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Sentiment Analysis and Human Activity Recognition Using Deep Learning in Social Networks and Sensor Data

Análise de Sentimentos e Reconhecimento de Atividades Humanas Utilizando Deep Learning em Redes Sociais e Dados Sensoriais

Campinas

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Tese apresentada à Faculdade de Engenharia Elétrica e de Computação da Universidade Estadual de Campinas como parte dos requisitos exigidos para a obtenção do título de **Doutor** em **Engenharia Elétrica**, na área de **Telecomunicações e Telemática**.

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Supervisor: **Prof. Dr. Yuzo Iano**

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Imagination is more important than knowledge. For knowledge is limited, whereas imagination embraces the entire world, stimulating progress, giving birth to evolution. (Albert Einstein).

Resumo

Esta tese explora a implementação e o impacto da tecnologia 5G na América do Sul, a análise de sentimentos das eleições presidenciais equatorianas e as metodologias avançadas para Reconhecimento de Atividade Humana (HAR) usando modelos de aprendizado profundo. A pesquisa começa examinando o status atual da implementação do 5G na América do Sul, com foco em países como Brasil, Equador, entre outros. O potencial da tecnologia 5G para transformar a infraestrutura digital e apoiar aplicações em cidades inteligentes é amplamente discutido.

A seguir, a tese apresenta uma análise de sentimentos das eleições presidenciais equatorianas, utilizando dados do Twitter (agora chamado de X) para examinar a opinião pública. Aproveitando a maior largura de banda e a menor latência do 5G, o estudo facilita a análise de sentimentos em tempo real, fornecendo insights oportunos sobre o sentimento público. A integração de análises avançadas de dados e modelos de aprendizado de máquina desempenha um papel crucial na interpretação da grande quantidade de dados gerados durante as eleições, destacando a relevância dessas tecnologias na análise política moderna.

A pesquisa então faz uma análise comparativa das abordagens baseadas em CNN-LSTM para Reconhecimento de Atividade Humana (HAR). Esta seção avalia diferentes metodologias e sua eficácia em reconhecer atividades humanas complexas, fornecendo descrições detalhadas das estruturas das camadas dos modelos e discutindo a importância do ajuste de hiperparâmetros para melhorar o desempenho. Além disso, a implementação prática dos modelos CNN-LSTM para HAR é discutida, com foco em métricas de desempenho como precisão, recall e F1-scores entre diferentes classes. A eficácia desses modelos em reconhecer com precisão as atividades humanas é demonstrada, o que é crucial para aplicações em saúde, segurança e interação homem-computador.

Os resultados obtidos ao longo da tese ressaltam o impacto transformador da tecnologia 5G e dos modelos avançados de aprendizado de máquina em vários setores. Além disso, os modelos CNN-LSTM alcançaram alta precisão no reconhecimento de atividades humanas, com métricas significativas de precisão e recall entre diferentes classes, demonstrando seu potencial em aplicações do mundo real. Esta tese contribui para uma compreensão mais profunda de como tecnologias emergentes como o 5G e modelos avançados de aprendizado profundo podem ser aproveitados para enfrentar desafios do mundo real e impulsionar a inovação em múltiplos domínios.

Palavras-chaves: 5G; ciência de dados; tweets; Reconhecimento de Atividade Humana; CNN-LSTM.

Abstract

In this thesis, the deployment and impact of Fifth Generation (5G) technology in South America, sentiment analysis of Ecuadorian presidential elections, and methodologies for Human Activity Recognition (HAR) using deep learning models were explored. This research begins by examining the current status of 5G in South America, with a focus on countries like Brazil, Ecuador, Peru and others. Further, the potential of 5G in order to transform digital infrastructure and support smart city applications was discussed. Later, this thesis shows a sentiment analysis of the Ecuadorian presidential elections, using data from Twitter (now called X) to examine public opinion. By leveraging the increased bandwidth and reduced latency of 5G, the study facilitates real-time sentiment analysis. The integration of data analytics and machine learning models plays a crucial role in interpreting the vast amount of data generated during the Ecuadorian's elections, highlighting the relevance of these technologies in modern political analysis. The study proceeds with a comparison of CNN-LSTM-based methods for Human Activity Recognition (HAR). This section evaluates different approaches for identifying human activities, providing a detailed breakdown of the model layer structures and emphasizing the importance of hyperparameters in performance optimization. Practical applications of CNN-LSTM models for HAR are also explored, highlighting performance metrics such as F1-scores, precision, and recall across various classes. It was demonstrated that these models can reliably identify human behaviors, which is crucial in fields like security, healthcare, and human-computer interaction.

The findings of this thesis highlight the impact of machine learning models and 5G technology across multiple industries. Additionally, the CNN-LSTM models showed significant potential in real-world applications, achieving high accuracy in human activity recognition with strong precision and recall across various categories. This work contributes to a deeper understanding of how cutting-edge technologies, like 5G and deep learning models, can address practical challenges and drive innovation across various sectors.

Keywords: 5G; data science; tweets; Human Activity Recognition; CNN-LSTM.

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List of Abbreviations, Acronyms, and Initialisms

Abbreviation	**Connotation**
5G	Fifth-generation mobile networks
4G	Fourth-generation mobile networks
IoT	Internet of Things
LTE	Long Term Evolution
AI	Artificial Intelligence
eMBB	enhanced Mobile Broadband
URLLC	Ultra-Reliable Low-Latency Communications
mMTC	massive Machine-Type Communications
ENACON	Ente Nacional de Comunicaciones
DSS	Dynamic Spectrum Sharing
ANATEL	Agência Nacional de Telecomunicações
ITU	International Telecommunication Union
ARCEP	Autorité de Régulation des Communications Électroniques
CONATEL	Comisión Nacional de Telecomunicaciones
FWA	fixed wireless access
MTC	Ministry of Transport and Communications
ANTEL	Administración Nacional de Telecomunicaciones
URSEC	Regulatory Unit of Communication Services
UNES	Unión por la Esperanza
CREO	Creando Oportunidades
API	Application Programming Interface
IDE	Integrate Development Environment
CSV	Comma Separated Values
NLTK	Natural Language Toolkit
CNN	Convolutional Neural Network
LSTM	Long Short-Term Memory
HAR	Human Activity Recognition
GNN	Graph Neural Networks
GCN	Graph Convolution Networks
SVM	Support Vector Machine
RNN	Recurrent Neural Networks
LRCN	Long-Term Recurrent Convolutional Networks

List of Symbols

Symbols	**Connotation**
P	Probability
x_t	Input tensor
t	Time step
$t-1$	Previous time step
h_t	Hidden state
c_t	Cell state, memory cell
f_t	Forget gate
i_t	Input gate
O_t	Output gate
W_i	Convolutional input gate
W_f	Convolutional forget gate
W_c	Convolutional memory gate
W_o	Convolutional output gate
b_i	Bias input gate
b_f	Bias forget gate
b_c	Bias memory gate
b_o	Bias output gate

Contents

1 Introduction

5G technology represents a revolutionary advancement in telecommunications, heralding unparalleled improvements in connectivity, speed, and capacity. This leap forward is poised to profoundly influence numerous sectors worldwide, with significant repercussions for data science and artificial intelligence (AI). This section explores the current state of 5G deployment on a global scale, examines its progress in Latin America with a particular focus on Ecuador, and highlights the transformative potential of 5G in enhancing data science and AI applications, including sentiment analysis and human activity recognition.

1.1 Global Situation of 5G Technology

The deployment of 5G technology is rapidly advancing worldwide, significantly transforming the telecommunications landscape. By 2025, 5G networks are projected to cover a third of the global population, with over 1.8 billion connections (GSM, 2024). Leading regions in 5G adoption include North America, Europe, and Asia-Pacific, with developed nations such as the United States, South Korea, and China at the forefront. These regions are spearheading 5G implementation due to the growing demand for faster and more reliable internet services (3GPP, 2020). In contrast, many European markets are progressing at a slower pace, and numerous countries in the region have yet to deploy 5G technology extensively. Meanwhile, in Latin America, 5G technology is in its nascent stage. Currently, the adoption rate of 5G in the region stands at approximately 5% of total connections. This figure is expected to increase to 14% by 2025, with Argentina, Brazil, Chile, Mexico, Guatemala, and Uruguay achieving a double-digit share of 5G connections by then (INTELLIGENCE, 2021). In the latter half of the decade, 5G adoption is anticipated to accelerate as new 5G markets emerge and existing networks expand into new areas.

1.1.1 5G in Latin America

In Latin America, the adoption of 5G technology varies significantly across countries. Brazil, Mexico, and Chile are leading the way with active 5G networks and ongoing expansion plans (INTELLIGENCE, 2021). Ecuador, while not a front-runner in adoption, is making notable strides towards implementing this technology. The Ecuadorian Ministry of Telecommunications and Information Society "MINTEL" has laid out a strategic plan to achieve nationwide 5G coverage by 2026, acknowledging the potential of 5G to drive digital transformation and economic growth (TELECOMMUNICATIONS; (MINTEL), 2020). The country has launched some pilot projects in major cities such as Quito and Guayaquil to test and refine 5G technology. For instance, the collaboration between the Ecuadorian government and Huawei has established 5G test zones in Quito, aimed at demonstrating 5G capabilities in real-world settings (HUAWEITECH, 2021). The partnership between the government and both international and local stakeholders aims to build a robust 5G infrastructure, positioning Ecuador as a regional leader in the digital age. The economic impact of 5G in Ecuador is expected to be substantial. According to a report by the Inter-American Development Bank (IDB), the adoption of 5G could increase Ecuador's GDP by 1.4% by 2030, driven by productivity improvements and new business opportunities in sectors such as agriculture, healthcare, and manufacturing (IDB, 2021).

1.2 The Impact of 5G on Data Science

The advent of 5G technology is set to revolutionize data traffic and data science. Mobile data traffic in Latin America is expected to grow at an average annual rate of 25.5% between 2023 and 2030, reaching over 24 exabytes (EB) per month by the end of the decade. On a per-connection basis, monthly mobile data traffic in Latin America is projected to increase from 7 GB to 32 GB during this period (ERICSSON, 2020). The development of new services like extended reality (XR) may accelerate the rise in mobile data traffic. Presently held by about 5% of users, XR gadgets are anticipated to have a rise in acceptance as more businesses enter the market with goods like Apple's Vision Pro. It is expected that Apple's developments in hardware, content, and user experience would stimulate the XR ecosystem, leading to more competition and maybe assisting in the metaverse's general development (GSM, 2024).

Because of 5G's high speed and low latency, real-time data processing and transmission are made easier, allowing for more advanced and fast data analysis. Applications that require instantaneous data handling, such sentiment analysis of social media data, will particularly benefit from this. For instance, 5G's increased bandwidth and reduced latency can facilitate real-time sentiment analysis of tweets, offering more accurate and timely insights into public opinion and trends (CAI *et al.*, 2019). Moreover, 5G enables edge computing, which is the processing of data closer to the data source. As a result, centralized data centers have reduced stress and delay, facilitating faster decision-making and more efficient use of network resources. Enhanced connectivity facilitates the integration of advanced data analytics tools and machine learning models, hence promoting innovation in sectors such as industry, transportation, and healthcare (GARTNER, 2021). There is a big influence of 5G on data storage. Rapidly moving massive datasets to and from cloud storage platforms improves the effectiveness of data workflows and facilitates scalable applications. Organizations may better manage and analyze massive amounts of data thanks to this change from localized to distributed data storage methods, which opens up new insights and competitive benefits. According to (SAJID, 2024), 75% of data generated by enterprises will be created and processed outside of traditional data centers or cloud settings. This highlights the significance that 5G will play in enabling this development.

1.3 Integration of 5G and Artificial Intelligence

The amalgamation of 5G and artificial intelligence (AI) presents significant opportunities for innovation in a multitude of fields. Large datasets and a lot of processing power are needed for AI applications to train and infer. These procedures are accelerated by 5G networks' increased data throughput and decreased latency, which permits quicker AI model deployment and training (REVIEW, 2020). 5G offers considerable advantages for real-time AI applications like personalized healthcare, predictive maintenance, and driverless cars. For instance, 5G's low latency guarantees that autonomous cars can interpret information from their environment quickly, improving efficiency and safety (CAI *et al.*, 2019). Predictive maintenance solutions, on the other hand, are able to optimize maintenance schedules and anticipate equipment failures in real-time in smart factories.

One prominent example of an AI application is Human Activity Recognition (HAR). HAR systems employ AI to understand and classify human movements based on sensor data. HAR apps can interpret real-time data from environmental sensors or wearable devices more effectively thanks to 5G's high bandwidth and low latency. This feature is very helpful in the sports industry for performance analysis, the healthcare industry for monitoring patient activities, and the security industry for investigating questionable conduct. The combination of 5G and AI has the potential to have significant socioeconomic benefits in Ecuador. Smart systems and better connection can improve public services, healthcare, education, and agriculture. For example, 5G and AI-powered smart healthcare solutions could improve healthcare accessibility and results by providing remote diagnostics and telemedicine services to underserved rural populations (DU *et al.*, 2020). AI-driven analytics in agriculture can improve resource management and agricultural yields, promoting sustainable practices and food security.

1.4 Dissertation Structure

For better understanding, the structure of dissertation is as follows:

- Chapter 2 reviews the current status of 5G in South America, focusing on its deployment, challenges, and advancements within the region.
- Chapter 3 presents a sentiment analysis on the political context of the Ecuadorian presidential elections, utilizing tweets from the Twitter platform to assess public opinion.
- Chapter 4 provides a comparative analysis of CNN-LSTM-based approaches for Human Activity Recognition, evaluating different methodologies used for this type of analysis and their effectiveness.
- Chapter 5 discusses the implementation of CNN-LSTM for Human Activity Recognition, highlighting the practical aspects and performance of the proposed solutions.
- Finally, Chapter 6 addresses the key conclusions of the dissertation and outlines directions for future research.

2 Revision of the 5G in South America

In the intricate tapestry of urban evolution, the advent of fifth-generation mobile networks (5G) emerges as a powerful force reshaping the landscape of digital experiences and, by extension, the blueprint of smart cities. Beyond the promise of accelerated upload and download speeds, 5G introduces a paradigm shift by ensuring minimal latency and the simultaneous connectivity of a multitude of devices.

The heartbeat of this transformation lies in the remarkable reduction of latency, with 5G boasting a mere 10 ms—half that of its predecessor, 4G—and the potential to reach an astounding 1 ms in optimal conditions, propelling data transfer into the realm of real-time communication. Importantly, as the number of connected devices surges into the tens of thousands, 5G maintains both speed and latency, signaling its capacity to support a significantly higher connection density.

This convergence of high connection density and low latency promises to revolutionize urban environments. Traditionally crowded spaces, where connectivity falters, will be transformed by 5G's capability to simultaneously link up to 1 million devices per square kilometer. This extends far beyond personal devices, encompassing a vast array of objects, sensors, and devices seamlessly exchanging information and communicating with each other.

The narrative deepens with an exploration of 5G's simplicity and low energy consumption—fundamental attributes unlocking the deployment of Internet of Things (IoT) applications. Through the removal of obstacles to IoT growth, 5G releases its potential in a variety of contexts, including public spaces, workplaces, and residential and outdoor areas.

Looking at things more broadly, 5G technology not only makes the development of smart cities a reality but also opens up a wide range of new uses. Smart cities dramatically raise key life quality indicators by utilizing data, technology, and digital solutions. These indicators range from crowd management and emergency response to traffic rules, street lighting, smart parking, and air quality monitoring and energy usage optimization. This includes less waste and water residue, quicker emergency response times, fewer healthcare expenses, less hazardous pollutants, and enormous economic possibilities.

While these innovations flourish in European landscapes through initiatives like Horizon 2020 and the Digital Single Market strategy, the story in South America takes a different turn. Most countries in the region are still at the initial pilot test stages of 5G deployment, hindered by legal and technical obstacles compounded by the far-reaching effects of the COVID-19 pandemic. Yet, these nations are in the process of governmental reforms, planning communication law revisions, and orchestrating frequency auctions, laying the groundwork for mobile operators to usher in 5G services to end customers. As the urban fabric of South America undergoes this transformative journey, the fusion of technology and society promises a future where connectivity and innovation intertwine to redefine the very essence of urban living.

2.1 Theorical Concepts

The most recent generation of mobile communication technologies to replace 4G (LTE/WiMax) is known as 5G, or fifth-generation mobile networks. When compared to its predecessors, it offers a major improvement in terms of speed, responsiveness, and connectivity. The following are some essential ideas related to 5G:

- **Latency Revolution:** Central to the theoretical underpinnings of 5G is its revolutionary approach to latency reduction, a concept well-established in the scientific domain (ANDREWS *et al.*, 2014). A paradigm shift toward real-time communication is shown by the achievement of latency as low as 1 ms in ideal circumstances (ANDREWS *et al.*, 2014). Applications requiring immediate responsiveness, such as dynamic industrial processes and mission-critical healthcare systems, require this theoretical leap.
- **High Density Connectivity and Urban Repurposing:** According to research investigations, the combination of low latency and high connection density lays out a theoretical terrain that has the potential to transform urban surroundings (BOCCARDI *et al.*, 2014). These articles offer insights into how 5G could revolutionize the connection paradigm in densely populated areas like stadiums by supporting up to 1 million devices per square kilometer concurrently (BOCCARDI *et al.*, 2014). This theoretical development represents a significant change in the way cities operate, enabling a smart infrastructure that can easily integrate a wide range of devices and sensors.
- **Simplicity, Low Energy Consumption, and IoT Synergy:** The deployment of Internet of Things (IoT) applications is greatly aided by the theoretical underpinnings of 5G technologies, which are simple and low energy consumption (**??**). This has been widely discussed in the scientific literature. These theoretical constructs remove hindrances to IoT development, allowing for the full realization of interconnected devices across diverse settings, including homes, industrial facilities, public spaces, and streets.

- **Smart Cities: Bridging Theory and Reality:** The theoretical constructs of smart cities find tangible expression through the implementation of 5G, as highlighted in scholarly works (GOHAR; NENCIONI, 2021). Scientific literature envisions improved air quality monitoring, energy optimization, traffic management, street lighting, smart parking, crowd management, and rapid emergency response as theoretical facets (GOHAR; NENCIONI, 2021). The practical deployment of 5G technology serves as the bridge between these theoretical concepts and their realization, substantially enhancing key quality-of-life indicators.

The idea of an intelligent metropolis mostly appeared in science fiction throughout the 20th century, as shown in popular culture. But as smart devices and advanced technology become more widely used, the once-fantastic notion that a city may develop intelligence and even consciousness is quickly becoming a reality (BATTY *et al.*, 2012). Information and communication technology integration is creating urban landscapes that are very different from earlier attempts. Smart cities are frequently depicted as networks of linked devices, like constellations, that continuously collect information on the movement of people and goods. The decision-making mechanisms that influence the city's social and physical features depend heavily on this data (BATTY *et al.*, 2012). The essence of the Internet of Things (IoT) lies in these instruments and their communication methods.

In the context of IoT device and application connection, it is imperative to acknowledge that 5G forms the basis of this system and is critical to the advancement of smart city development (RAO; PRASAD, 2018). The fifth generation (5G) of wireless transmissions is a paradigm change that not only showcases technological improvements over the fourth generation (4G) networks, but also expands their reach into new sectors like artificial intelligence and the Internet of Things (FUENTES *et al.*, 2020).

The introduction of 5G is expected to offer three core services, each with its own set of technical specifications: enhanced mobile broadband (eMBB), ultra-reliable low-latency communications (URLLC), and massive machine-type communications (mMTC) (FUENTES *et al.*, 2020). These services are tailored to particular use cases and applications. For instance, eMBB is designed for multimedia access, including high-resolution films and augmented reality. URLLC is designed for applications like industrial automation and unmanned vehicles where minimal latency is essential. Meanwhile, mMTC is essential in situations where a substantial number of connected devices is a paramount requirement, directly tying into the context of smart cities (NAVARRO-ORTIZ *et al.*, 2020).

While there's a tendency to associate smart cities primarily with mMTC services, it's essential to emphasize that the spectrum of services and applications contributing to a smart city is vast. Smart city applications can be categorized into those enhancing city infrastructure, those improving the quality of life for residents (social and economic well-being), and those enhancing overall city management (RAO; PRASAD, 2018).

Examining the aforementioned services, it becomes evident that a smart city can leverage the full spectrum of capabilities offered by 5G. For instance, eMBB finds application in services requiring real-time video transmission, such as surveillance with cameras and remote educational classes. URLLC proves to be invaluable for systems overseeing the distribution of water, gas, and power, and it also serves a critical role in traffic control. Additionally, URLLC holds potential for future applications in communication among unmanned vehicles. Given the multitude of devices—sensors, actuators, and others—interconnected within a smart city, mMTC emerges as an indispensable component. The seamless functioning of a smart city relies heavily on the secure exchange of information between many devices and systems. 5G introduces enhanced security features compared to its predecessors, incorporating robust encryption protocols, authentication mechanisms, and secure network architectures.

2.2 Analysis of 5G in South America

This section provides a comprehensive examination of the implementation of 5G across the diverse countries and territories of South America as Argentina, Ecuador, Brazil, Chile, Colombia, Guyana, Paraguay, Peru, Suriname, Uruguay, Venezuela, Bolivia, and includes the French Guiana territory. Drawing upon the latest information gathered from governmental agencies, websites, and specialized media outlets over the past three years, this section delves into the evolving landscape of 5G deployment. The purpose is to underscore the significance of this topic, offering insights into the advancements and trends shaping the region's telecommunications infrastructure.

2.2.1 Argentina

A 5G technology demonstration was launched in March 2021 by the National Communication Entity (ENACON), which invited information and communication technology industry participants to promote the features of 5G(NADA,). The event will be attended by national authorities, representatives from providing companies, and specialized journalists. During the showcase, the potential applications of the new technology in various domains will be demonstrated. Additionally, Buenos Aires and Rosario became the first cities in the country to receive the 5G network, employing Dynamic Spectrum Sharing (DSS) to utilize the 4G spectrum (ECONOMISTA, 2021).

2.2.2 Bolivia

Entel, the state-owned telecom company in Bolivia, organized a test event to carry out the first 5G trials in the nation. It is expected that its implementation will take place piecemeal throughout the region, starting with La Paz, Cochabamba, and Santa Cruz (MASCONTAINER, 2020). Nevertheless, official sources from the Bolivian Ministry of Telecommunications detailing the progress of this project could not be located.

2.2.3 Brazil

The National Telecommunications Agency (ANATEL) authorized the radio-frequency band auction in February 2021 in order to enable the delivery of 5G technology-based telecommunications services in Brazil (ANATEL, a). The auction encompasses frequencies such as 700 MHz, 2.3 GHz, 3.5 GHz, and 26 GHz, exclusively allocated for 5G use, with specified conditions for the winning bidders. While the auction is pending, telecommunications operators already operating in Brazil are introducing 5G DSS, a technology that shares the spectrum currently utilized by 4G LTE (SPADINGER, 2021).

This progress will be overseen by a working committee inside the lower house of the National Congress, working with officials from ANATEL, the Ministry of Communications, the Ministry of Science and Technology, and both large and small internet service providers (ANATEL, b).

2.2.4 Chile

In February 2021, Chile successfully concluded the inaugural auction dedicated to implementing 5G technology in Latin America (SUBTEL, 2023). The auction specified the companies entrusted with the 26 GHz, 3.5 GHz and 700 MHz frequency bands. The victorious companies are mandated to ensure coverage for 199 hospitals, 24 ministries, 16 stewardships, 16 regional capitals, and 56 provincial capitals. Additionally, they have the option to extend coverage to 17 airports, 12 public interest centers, 28 higher education institutions, and 23 seaports (SUBTEL, 2023). A maximum three-year schedule for the technology's deployment is outlined in the bidding procedure, with 100% coverage for hospitals within the first year, 100% coverage for required places within 18 months, and 88% coverage for municipalities (taking into account all auctioned bands) within the same 18 months.

2.2.5 Colombia

In December 2019, Colombia's Ministry of Information and Communications Technologies (Min. ICT) introduced the 5G Adoption Action Plan (ARBELáEZ, 2020), designed to pinpoint regulatory hurdles hindering the deployment and operation of 5G and conduct preliminary tests.

In September 2020, the government initiated test pilots by granting temporary permits to participants for evaluating 5G technology. Conversely, as per the Action Plan, the allocation of the 3.5 GHz band is anticipated to occur by the third quarter of 2021. Notably, specific regulations for 5G have yet to be developed. As outlined in the 5G Adoption Action Plan, regulatory adjustments are slated for implementation by the second quarter of 2021 (ARBELáEZ, 2020).

2.2.6 Ecuador

As part of the government project known as Digital Ecuador, the Ministry of Telecommunications stated that Ecuador was originally planning to roll out 5G technology in 2020. However, the rollout of 5G in the nation was beset by delays because of restrictions related to the pandemic and the lack of laws controlling spectrum usage. To help with the deployment of 5G, the Minister of Telecommunications requested in 2021 that the International Telecommunication Union (ITU) assess the 3.5 GHz spectrum. The forthcoming Ecuadorian administration will use these assessments as vital information to start the competitive process of renegotiating contracts with mobile phone providers, opening the door for the rollout of 5G technology (PRIMICIAS, 2024).

Some cellular providers have stated that the cost of radio spectrum is the main barrier to 5G deployment in Ecuador. This could prevent 5G from being fully utilized and then integrated into smart cities. Conversely, the Ecuadorian mobile operator CNT chose to partner with telecommunications company Nokia to help roll out the nation's first 5G network using a Non-Standalone 5G (NSA 5G) strategy. As a result, Guayaquil and Manta will host the first NSA 5G stations, which will allow CNT to plan its 5G services with improved characteristics like ultra-low latency, connectivity, and capacity. It is anticipated that this strategy will improve cost effectiveness, simplify processes, and lessen complexity.

2.2.6.1 Mobile Data in Ecuador

Ecuador has seen a significant rise in the use of mobile data in recent years; this trend has been clearly observed by the study of bandwidth by protocol using Sandvine monitoring software. The rise in popularity of video applications, which are all the rage on digital platforms like Facebook Video, Instagram Video, TikTok, and others, is directly related to this spike. It is more important than ever to increase data speeds and guarantee dependable connectivity for all customers as Ecuador draws closer to the widespread adoption of 5G technology.

The data from Sandvine's monitoring software analysis paints a vivid picture of Ecuador's present mobile data consumption situation. According to the data, video applications are by far the biggest users of bandwidth, far surpassing the usage of other online activities. Although the move toward video content is not surprising globally, it is especially noticeable in Ecuador, where sites like Facebook Video, Instagram Video, and TikTok have become indispensable for daily digital interactions.

The prominent protocols influencing data consumption in Ecuador are highlighted in Figure 2.1, which shows the bandwidth by protocol for mobile data usage in 2022. Due to a relocation of the Sandvine monitoring system, the data was collected from October 15, 2022, to December 31, 2022. Facebook Video is seen as a major role, with bandwidth usage peaking at an astounding $60,000,000,000$ bits per second. The platform's widespread appeal and the strong demand for video content are highlighted by this significant data usage. Furthermore, TikTok and WhatsApp Media are also heavily included, which reflects the expanding trend of media consumption and video sharing on mobile devices. These findings highlight how important video apps are in determining how much data is used on mobile devices and how a strong infrastructure is required to meet this demand.

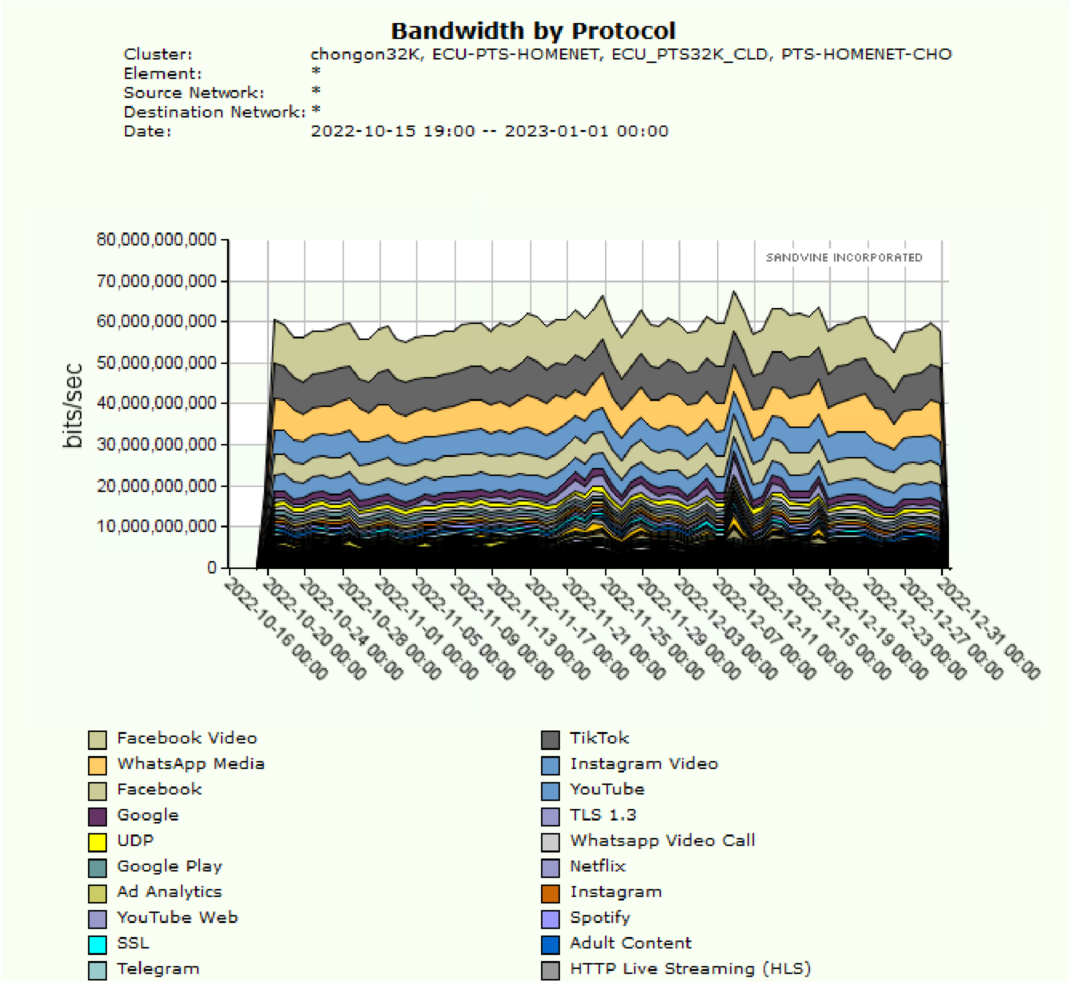

Figure 2.1 – Mobile Data of 2022

The top protocols influencing data consumption in Ecuador are shown in Figure 2.2, which displays the bandwidth by protocol for mobile data usage in 2023. With bandwidth use reaching an astounding $70,000,000,000$ bits per second, TikTok has emerged as the leader, demonstrating both its expanding dominance and the growing demand for short-form video content. Apps for sharing videos and other media are still quite popular, as seen by the prominence of Facebook Video, WhatsApp Media, and Instagram Video. This development underscores the imperative necessity for growing data needs propelled by these extensively utilized platforms, underscoring the significance of 5G technology in guaranteeing uninterrupted connectivity and fast access for every user.

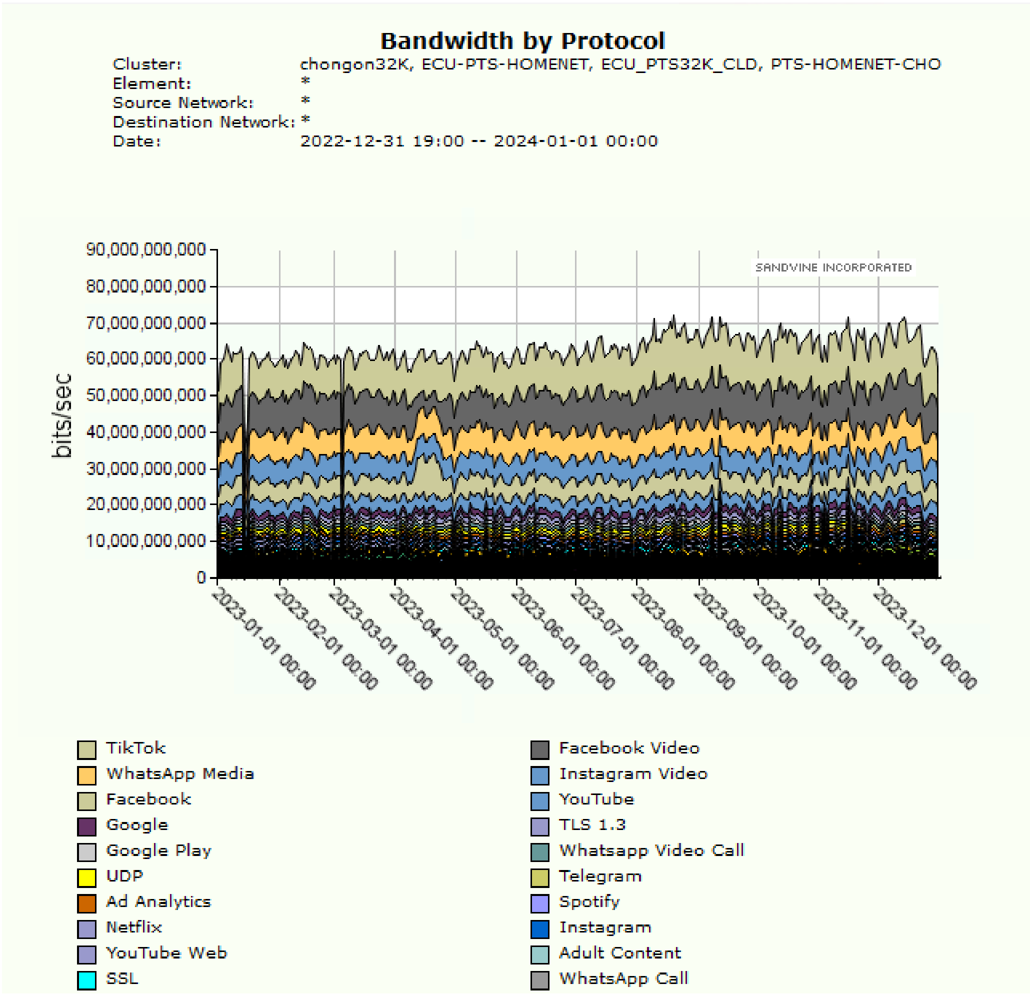

Figure 2.2 – Mobile Data of 2023

The bandwidth by protocol for mobile data usage from January 1 to June 1, 2024 is shown in Figure 2.3, which also highlights the main protocols influencing data consumption in Ecuador. TikTok is still in the lead, as evidenced by its highest bandwidth usage of 78,000,000,000 bits per second, which highlights both its increasing power and the enduring appeal of short-form video content. The fact that Facebook Video, Instagram Video, and WhatsApp Media are all heavily featured suggests that there is still a strong need for people to share and consume media on mobile devices. The importance of video applications on mobile data usage patterns is highlighted by these studies. Platforms like Facebook Video, Instagram Video, WhatsApp Media, TikTok, and others consume a lot of data, which emphasizes the need to improve infrastructure to keep up with these demands. It is vital to allocate resources towards 5G technologies in order to furnish the requisite bandwidth and speed, guaranteeing users uninterrupted, superior video streaming and media sharing experiences.

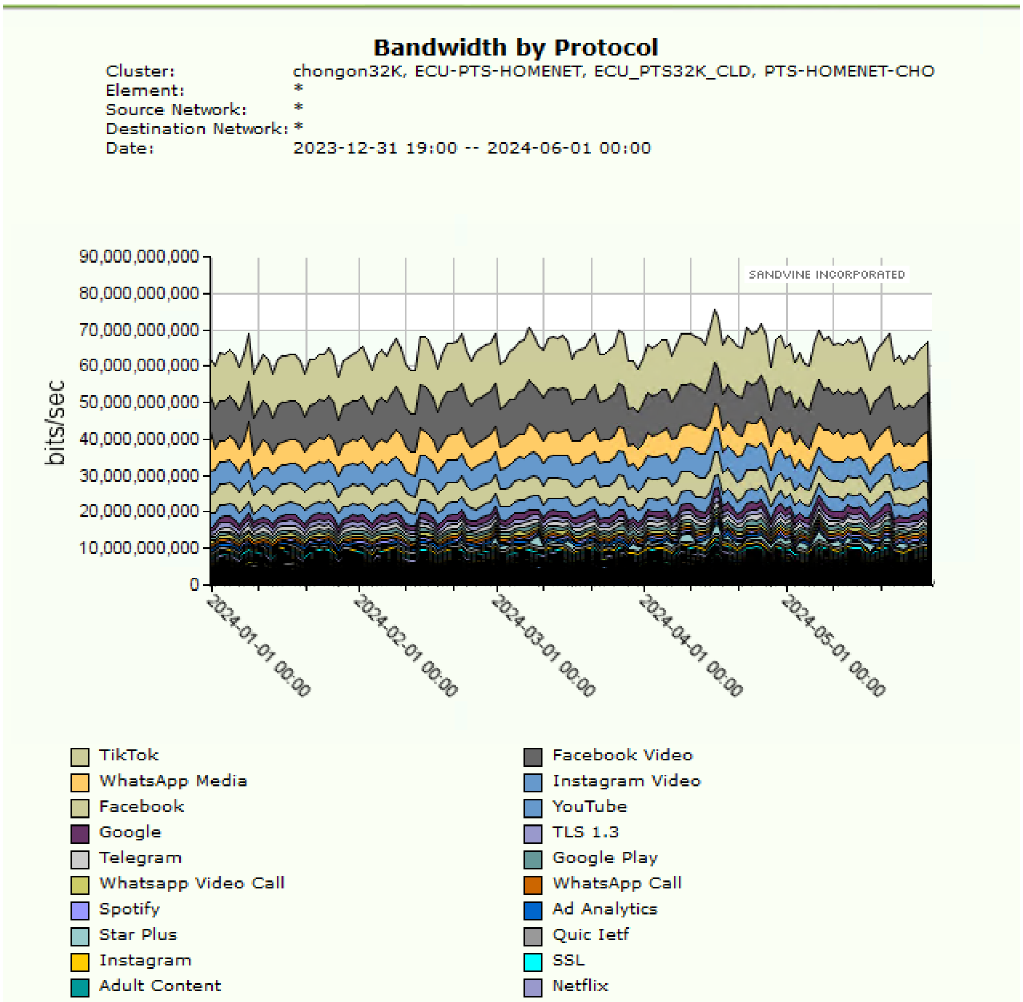

Figure 2.3 – Mobile Data of 2024

The data from Sandvine's monitoring software analysis paints a vivid picture of Ecuador's present mobile data consumption situation. According to the data, video applications are by far the biggest users of bandwidth, far surpassing the usage of other online activities. Although the move toward video content is not surprising globally, it is especially noticeable in Ecuador, where sites like Facebook Video, Instagram Video, and TikTok have become indispensable for daily digital interactions.

- TikTok: A platform well-known for its brief yet captivating videos, has emerged as a significant force in the world of video entertainment. Because of its algorithm-driven content delivery, users are guaranteed to be engaged at all times, which results in prolonged usage and significant data consumption.

- Facebook Video: As part of the broader Facebook ecosystem, Facebook Video offers users a mix of live streaming, pre-recorded content, and user-generated videos, contributing significantly to overall bandwidth usage.

- Instagram Video: With features like Stories, IGTV, and Reels, Instagram Video has created multiple avenues for users to consume and create video content, further driving up data usage.

These platforms are not just entertainment tools; they have also become essential for communication, education, and commerce, embedding themselves deeply in the digital habits of Ecuadorians.

Given the massive bandwidth consumption by video applications, the transition to 5G technology in Ecuador is both timely and necessary. 5G offers numerous advantages over previous generations of mobile technology, primarily in terms of speed, latency, and capacity.

2.2.7 Guyana

A formal memorandum of understanding has been established by the governments of Guyana and Brazil to carry out technical feasibility studies for the establishment of optical fiber connectivity between the capitals of Guyana and Brazil, Georgetown and Boa Vista, respectively (BRASIL,). A cooperative working group will be formed, and a representative from the Brazilian Ministry of Communications will be assigned to supervise the research (BRASIL,).

In the broader perspective, both governments aspire to deploy an optical fiber cable spanning 6,000 kilometers, enabling the transmission of 72 terabits of data per second in the long term (SOUZA, 2021).

2.2.8 French Guiana

Unlike other South American nations, French Guiana is a French colony subject to French laws and regulations. It is also overseen by the regulatory body ARCEP, which is in charge of enforcing communication laws throughout the region. Despite difficulties faced by the Chinese equipment maker Huawei, France launched its 5G network deployment on time in 2020. But since then, the inhabitants have been using and testing the implementation(REUTERS, 2019).

2.2.9 Paraguay

As per the president of the Telecommunications National Commission of the Republic of Paraguay (CONATEL), the frequencies allocated for 5G in the country are not expected to be auctioned before 2024. Until that time, these frequencies will be assigned for other services (BNAMERICAS, a). Nevertheless, this does not imply a lack of progress in Paraguay's digital transformation. The nation is actively constructing a nationwide optical fiber backbone, completing the initial phase in June 2020, with two additional phases underway (BNAMERICAS, b).

2.2.10 Peru

Peru has started the process of obtaining permissions to deploy 5G technology in a non-standalone configuration. The Ministry of Transport and Communications noted that this enables telecom providers to deploy 5G using current 4G LTE infrastructures and fixed wireless access (FWA). Within fixed broadband networks, FWA technology provides a mobile solution for last-mile connectivity (BNAMERICAS, c).

During initial tests conducted in collaboration with Huawei Technologies, the leading mobile services company achieved an impressive download speed of 3.3 Gbps (CLARO,). Simultaneously, in early 2021, the Ministry of Transport and Communications (MTC) of Peru announced the completion of the planning phase for an auction of the 3.5 GHz and 26 GHz spectrum. The ministry is set to reveal the details and timetable for the bidding process (CLARO,).

As stressed by the Ministry of Transport and Communications (MTC), Peru is actively pushing the implementation and acceptance of 5G, realizing the critical role that technology plays in the nation's economic recovery

2.2.11 Suriname

In November 2019, Telesur, the telecom operator in Suriname, unveiled its 5G network, making it the first of its kind in the Caribbean (TELESUR,). Telesur has not actively advertised its commercial 5G network up until now, despite it being operational in Paramaribo, the capital city, since December 2019. This is a result of the business's concentrated efforts to improve and supplement its service offerings by installing LTE-A updates in strategic places (BARTON, 2020).

2.2.12 Uruguay

In April 2019, Uruguay, in collaboration with Nokia through the National Administration of Telecommunications (ANTEL), achieved the distinction of becoming the first country in Latin America to commercially offer 5G Internet. The initial launch occurred in the cities of La Barra and Nueva Palmira, with plans for swift expansion nationwide (PRESIDENCIA,). Uruguay holds the status of being the third country globally to introduce this innovative technology, following South Korea and the USA. The service was first offered by the implementing business as an addition to optical fiber networks, with a focus on areas that were not yet served by broadband networks. Since no cellular device at the time supported the 5G network, this strategy was chosen (DIARIA,). Coordinated efforts between the Regulatory Unit of Communication Services (URSEC) and telecoms businesses in Uruguay began in October 2020 and are expected to end in March or April 2021. The purpose of the assessments is to determine what spectrum is available for the 5G network expansion. A bid for extra frequency bands will be opened if needed (MALEK, 2022).

2.2.13 Venezuela

President Nicolás Maduro has said that Venezuela will begin testing the installation of a 5G experimental telecommunications network. As he spoke from the Miraflores Palace at a ceremony honoring the 45th anniversary of diplomatic ties between China and Venezuela, the president stressed that "Venezuela is not falling behind; we are progressing with technology." More than 200 Chinese businesses are actively involved in contributing to and working for the nation's development (CONATEL, 2019).

The current landscape of 5G implementation in the South American region reflects a dynamic interplay of technological advancements, regulatory frameworks, and strategic collaborations. As evidenced by recent developments, several countries in South America have initiated significant steps towards the deployment of 5G networks, each encountering unique challenges and opportunities.

Brazil's strategic initiatives, as discussed in the comprehensive study by (COUTO *et al.*, 2022), exemplify the nation's commitment to advancing its telecommunications infrastructure. The auctioning of crucial frequency bands represents a significant leap forward in Brazil's journey toward 5G integration. Similarly, the practical insights gained from Colombian pilot tests, as detailed by (BARRIOS-ULLOA *et al.*, 2023), offer valuable perspectives on the on-the-ground realities of 5G deployment, providing a foundation for broader implementation strategies.

On the other hand, some nations have experienced delays. One example of this is Ecuador, where (PAZMINO *et al.*, 2023) notes that outside circumstances impacted the implementation timeframe. Nonetheless, as demonstrated by continuous attempts to construct a national optical fiber backbone, the country is still dedicated to its digital transformation.

Moreover, Uruguay (NOKIA, 2022) is a pioneer in Latin America thanks to the successful commercialization of 5G Internet in a few cities. Notably, close cooperation with leading industry players like Nokia has been added to the incorporation of 5G technology.

As we conclude this section, it is evident that South American nations are navigating the complex terrain of 5G implementation, balancing technological aspirations with regulatory considerations and international collaborations. The area is leading the way in a revolutionary era of communications, and more research will reveal the complex aspects of 5G rollout in South America.

3 Data Analysis

Social networks are becoming an essential part of the digitally connected world; they operate as virtual spaces where people interact dynamically with one other, with communities, and with organizations. These online platforms generate enormous amounts of data, which offer a wealth of information just waiting to be discovered and examined. Researchers, analysts, and companies looking to comprehend the nuances of relationships, information sharing, and human behavior are finding that social network data analysis is a potent tool.

This section explores the methods, difficulties, and learnings from examining the relationships and patterns found in these virtual ecosystems as it dives into the intriguing field of social network data analysis. The analysis of social network data provides a deep understanding of societal dynamics, enabling informed decision-making in sectors as diverse as public health, sociology, and marketing. It may also be used to detect trends in user behavior and anticipate the virality of content.

We will explore the significance of influential nodes, negotiate the intricacies of network architecture, and talk about the ethical issues surrounding the analysis of interpersonal relationships as we go along. In the era of social networks, this section seeks to shed light on the transformative potential contained within the vast sea of social network data. It also highlights the knowledge that can be gleaned from the depths of data analysis and the effectiveness of pre-processing, processing, and data analysis in locating information concealed within the data.

3.1 Sentiment Analysis in the Presidential Election of Ecuador

In a short amount of time, social media on the internet has quickly become a major platform for social interaction, a place to discuss hot subjects and share news and political data. Particularly, Twitter distinguishes itself as a microblogging network that allows users to share messages in real time, or "tweets," with a character restriction of 280 (YAQUB *et al.*, 2017). As a result, Twitter provides a wealth of user-generated linguistic data and presents a chance to apply sentiment analysis techniques to gain insightful understanding of public behavior.

Sentiment analysis is a computational process designed to discern emotions and feelings conveyed in textual content, seeking to comprehend the emotional nuances when users articulate their opinions. This approach makes use of methods that closely examine textual components and compare them to predetermined emotional patterns (SARLAN *et al.*, 2014). Twitter tweets are useful as indicators of individuals' positions on a range of topics because of their unique qualities and perspectives. Furthermore, terms that express particular emotions are often used in tweets (DÁVALOS, 2020).

A broad range of industries use sentiment analysis, although business and politics are two of the most popular ones. Using Twitter in conjunction with sentiment analysis techniques facilitates the examination of political campaigns, government operations, and the regions that favor a given candidate. This data is essential for planning strategies to increase electoral chances, win more votes, and obtain a competitive advantage in elections.

Several research in the fields of political science and electoral behavior (EDER *et al.*, 2017; WAGNER *et al.*, 2012; HENDRICKS *et al.*, 2010) seek to clarify the variables influencing people's choice of a certain candidate. Political and economic environments, public awareness of a candidate, the candidate's political stance, support from national authorities, debate performance, and polling results are among the main factors (HENDRICKS *et al.*, 2010; GILMORE, 2012).

To distinguish between accounts that were spam and those that weren't, a study of tweets from the 2014 Colombian presidential election was done in (CERÓN-GUZMÁN; LEÓN-GUZMÁN, 2016). The project also included a sentiment analysis system that investigated how social media might be used to predict voting intentions. (YAQUB *et al.*, 2017; BARGHUTHI; SAID, 2020; ANSARI *et al.*, 2020) analyze and identify significant elements of political discourse on Twitter during elections in the USA (2016), Turkey (2018), and India (2019). In these studies, a detailed analysis was done on Twitter data that was gathered prior to Election Day.

Online social networks were utilized extensively in the Ecuadorian electoral elections of 2021 to convey information about political parties and their proposals (UNIVERSO, 2021). This study focuses on the examination of tweets sent by Guillermo Lasso and Andres Arauz during the second round of the 2021 Ecuadorian presidential election, which was held from March 16 to April 8, 2021. The primary aim of this analysis is to discern the sentiment expressed in the candidates' tweets, comprehend their behavioral patterns, and establish associations with attributes present in their tweets. Additionally, the study explores prevalent discussion topics on Twitter within the accounts of both candidates.

3.1.1 The Second Round of the Presidential Election in Ecuador

On February 7, 2021, Ecuador conducted the first round of its presidential election, wherein citizens cast their votes to choose the president, assembly members, and Andean parliamentarians. After the first round ended, Andres Arauz of the UNES party was the clear winner with 32.72%, followed by Lasso of the CREO party with 19.74% and Pérez of the Pachakutic party with 19.39%. The 13 other contenders, null, and blank ballots shared the remaining votes.

To secure a first-round victory in the Ecuadorian election, a candidate must achieve either 40% of the votes with a lead of 10 points over the second candidate or more than 50% of the valid votes (CNE.GOB.EC, 2021). As none of the candidates met these criteria, Ecuador proceeded to a second-round presidential election between Arauz and Lasso from March 16 to April 8, 2021. This phase witnessed a significant uptick in Twitter activity, marked by a multitude of attacks, including fake news, defamation, and discrediting, from both candidates. Consequently, tweets featuring hashtags such as #LaBancaOElPaís, #AndrésNoMientasOtraVez, and #LassoEsMoreno gained traction during the second round of the presidential election (PRIMICIAS, 2021).

3.2 Methodology

The process used to examine and analyze the Twitter data produced by Ecuadorian candidates Lasso and Arauz is shown in Figure 3.1. This section will provide a thorough discussion of this workflow, which is broken down into separate parts.

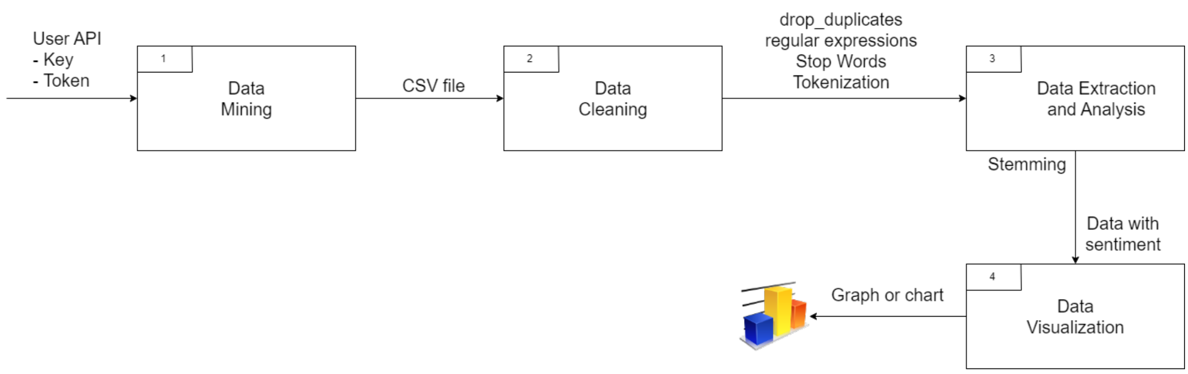

Figure 3.1 – The steps of the proposed work flow for the Ecuadorian election Twitter analysis.

3.2.1 Data Mining

Depending on the software utilized for collecting data from Twitter, numerous libraries and APIs from the social network itself are available. These tools facilitate the extraction of various attributes present in each user's tweet.

To access Twitter's proprietary API, one must register, specifying the purpose and reasons for data usage. Following registration, approval is required to obtain Keys and Tokens, enabling exploration and extraction of information.

This study utilized the Python development interface with Jupyter Notebook IDE, incorporating the tweepy library for data extraction. The focus was on identifying current trends in the political realm, specifically evaluating hashtags related to the Ecuadorian election campaign's second round, which occurred from March 6th, 2021, to April 8th, 2021.

The tweepy library furnished comprehensive information from each tweet, subsequently stored in a CSV (Comma Separated Values) file. The chosen fields for analysis within the CSV file were:

- "Text" in a tweet.
- The creation date of a tweet is "created at".
- Location of a tweet: "location".
- "Retweet retweet count" is the number of retweets.

3.2.2 Data Cleaning

Following the successful collection of tweets according to the desired trend, pre-processing was carried out to guarantee the best possible analysis. To enable precise analysis, the text of each tweet was cleaned, and variable formats were changed. To facilitate additional processing, the CSV file containing the gathered data was put into a pandas data frame.

The drop_duplicates program was used to remove duplicate tweets. This tool systematically evaluates each row in the selected column, seeking to delete duplicate entries from the dataset.

As part of a more extensive data pre-processing stage, a new function was then developed to sanitize the text using regular expressions. In order to find and eliminate whole text strings that matched this pattern, this involved extracting links connecting to external websites in the format http\S+. Punctuation, such as question marks, exclamation points, commas, and periods, was taken into account when developing the regular expressions because it can influence how tweet contexts are correctly understood.

The deletion of user mentions from tweets was also handled. Regular expressions in the format @\S+ were used to accomplish this, which made it easier to remove user names that were referenced in the tweet content. This thorough pre-processing method guarantees that clean, standardized textual data are used for the analysis that follows.

Lists of words intended for natural language text pre-processing are included in the NLTK package and are referred to as **StopWords**. Eliminating a preset list of words that don't substantially change a phrase's context is the main goal of employing StopWords. These words are usually made up of pronouns and articles. Eliminating these frequent language features assures that subsequent analyses are unaffected because they make very little contribution to the text's overall context. During analysis, the more significant and content-rich parts of the language are kept front and center by eliminating StopWords.

Once the prior text pre-processing steps are finished, the NLTK package's **Tokenization** functionality kicks in. After completing these preliminary processes, tokenization takes control and breaks down phrases into their individual words. Through this technique, the computer is able to examine the text word-by-word, allowing for a more detailed analysis of the linguistic content. Tokenization is essentially an important stage in converting textual material into a format that can be accessed by computers and is useful for detailed analysis.

3.2.3 Data Extraction and Analysis

After the initial pre-processing of the tweet texts, the next step involves subjecting the individual words to a stemming process. This process is instrumental in reducing words to their fundamental root forms by eliminating various linguistic inflections. For instance, words such as "retrieval," "retrieved," and "retrieves" are all streamlined to share the common root "retrieve" through the application of stemming.

By reducing words to their most basic form, stemming facilitates a more cohesive and significant representation, which is crucial for text analysis and natural language processing. By standardizing words to their roots, stemming aids in the recognition of common themes and patterns in the data, contributing to a more robust and effective analysis of the textual content.

3.2.3.1 Spanish Sentiment Analysis

We used the *sentiment-analysis-spanish* library, specifically version 0.0.25, to do sentiment analysis in Spanish. This library predicts feelings in Spanish phrases using a Naive Bayes classifier. The classifier was trained using a substantial dataset of 800000 comments extracted through web scraping from various platforms, including Decathlon, Tripadvisor, FilmAffinity, El Tenedor, and eBay. Remarkably, this training resulted in an impressive accuracy of 90% on the test dataset.

Equation 3.1, which represents the Naive Bayes classifier mathematically, captures the conditional probability. Here, the tokenized text is denoted by x, and the text class, c, represents the sentiment (positive or negative). The phrase's numerical values for each word make it simpler to determine if the word is more likely to fall into a good or negative sentiment category. This approach offers a complex and probabilistic interpretation of sentiments in the Spanish language, boosting the accuracy and reliability of the sentiment analysis results.

$$P(c \mid x) = \frac{P(x \mid c)\, P(c)}{P(x)} \tag{3.1}$$

For evaluated phrases, the *sentiment-analysis-spanish* library computes probabilities and assigns values on a scale from 0 to 1. The phrase is categorized as positive when the computed value becomes close to 1. Lower probability, on the other hand, suggest a negative attitude. Phrases that fall between 0.4 and 0.6 in this case study's context are classified as neutral. This nuanced approach allows for a more fine-grained interpretation of sentiments, enabling the identification of not only positive and negative but also neutral expressions within the analyzed text.

3.2.3.2 Sentiment Analysis and Translation into English

Due to the more advanced development of sentiment analysis libraries in the English language, the tweets initially extracted in Spanish underwent translation into English. To achieve this, the TextBlob library was employed, utilizing the Google Translate API for language translation. As the API imposes a daily limit on the number of translations, the tweet dataset was strategically divided to stay within the daily translation allowance.

Text polarity and subjectivity are evaluated by the sentiment analysis class in the natural language processing package TextBlob. The library assigns values between -1 and 1 for text polarity. A feeling that is close to one suggests positivity, and a sentiment that is close to -1 implies negativity. Neutral values in this study are those that are roughly equivalent to 0.

In addition to TextBlob, the analysis involved the use of the Vader library. Specifically designed for sentiment analysis in social networks, Vader is adept at processing text syntax prevalent in social media, including emoticons, colloquial language, and region-specific expressions. The library relies on lexicons and manually constructed dictionaries of phrases and words to enhance text classification.

Vader provides four values that represent the likelihood of a given phrase belonging to a specific sentiment, whether positive, negative, or neutral. This dual approach using TextBlob and Vader ensures a more comprehensive and accurate sentiment analysis, accounting for the nuances present in social media text expressions.

3.2.4 Data Visualization

The final stage illustrated in Figure 3.1 involves data visualization, a crucial step wherein pre-processed data or information is transformed into visually interpretable forms such as graphs, charts, or other visual representations. This step aims to provide a comprehensive and accessible overview of the processed data, facilitating a deeper understanding of patterns, trends, and insights. Data visualization enhances the communication of complex information and supports more informed decision-making by presenting data in an intuitive and visually engaging manner.

3.3 Results

This section is dedicated to scrutinizing the outcomes derived from implementing the methodology outlined in Section 3.2, specifically concerning the tweets disseminated by the candidates Arauz and Lasso.

The visualization illustrates the Twitter sources' origins, explaining the platforms where the tweets originated, as shown in Figure 3.2. In terms of both candidates, the Web App seems to be the primary source, followed by the iPhone mobile application. There is a noticeable difference in the use of Media Studio and Android mobile apps, with candidate Arauz demonstrating a smaller percentage. This discrepancy highlights the diverse resource channels employed by the candidates within the Twitter social network, offering insights into their strategic choices in leveraging different platforms for communication and engagement.

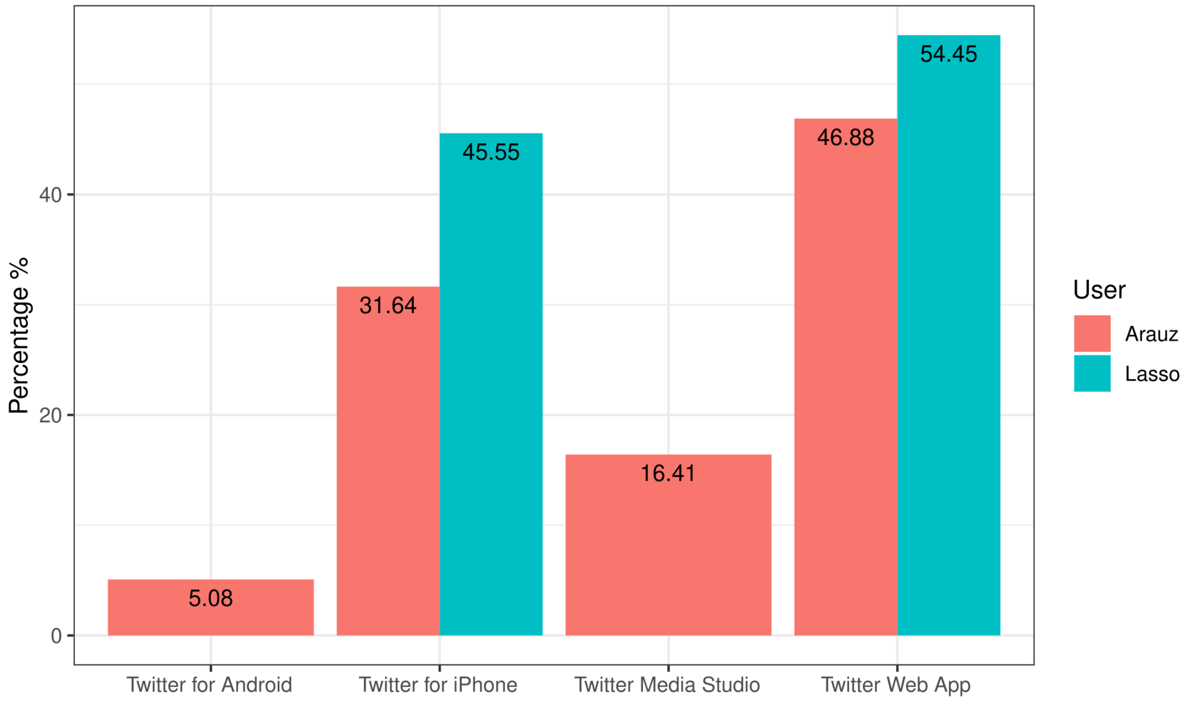

Figure 3.2 – Sources on Twitter that each candidate uses.

In Figure 3.3, an analysis of the tweet composition for both candidates is presented, focusing on the percentages of organic tweets, retweets, and replies. Notably, candidate Arauz stands out with a substantial 76.95% of his tweets being organic, indicating a higher level of direct engagement in crafting original content. In contrast, candidate Lasso's organic tweets constitute a more modest 7.99% of his overall tweet volume.

Additionally, a distinctive trend emerges in the tweeting behavior of candidate Lasso, where a significant portion 91.55% comprises replies to tweets in which he is mentioned. This suggests a heightened level of interaction between candidate Lasso and Twitter users, reflecting a more responsive and engaged presence. This interaction-driven approach is further emphasized by the relatively low percentage of retweets in candidate Lasso's profile compared to candidate Arauz. The rationale here is that a Twitter account solely focused on retweeting without contributing individual content may not resonate as strongly with the user base. Candidate Lasso's strategic mix of replies and original tweets underscores a nuanced and effective engagement strategy on the platform.

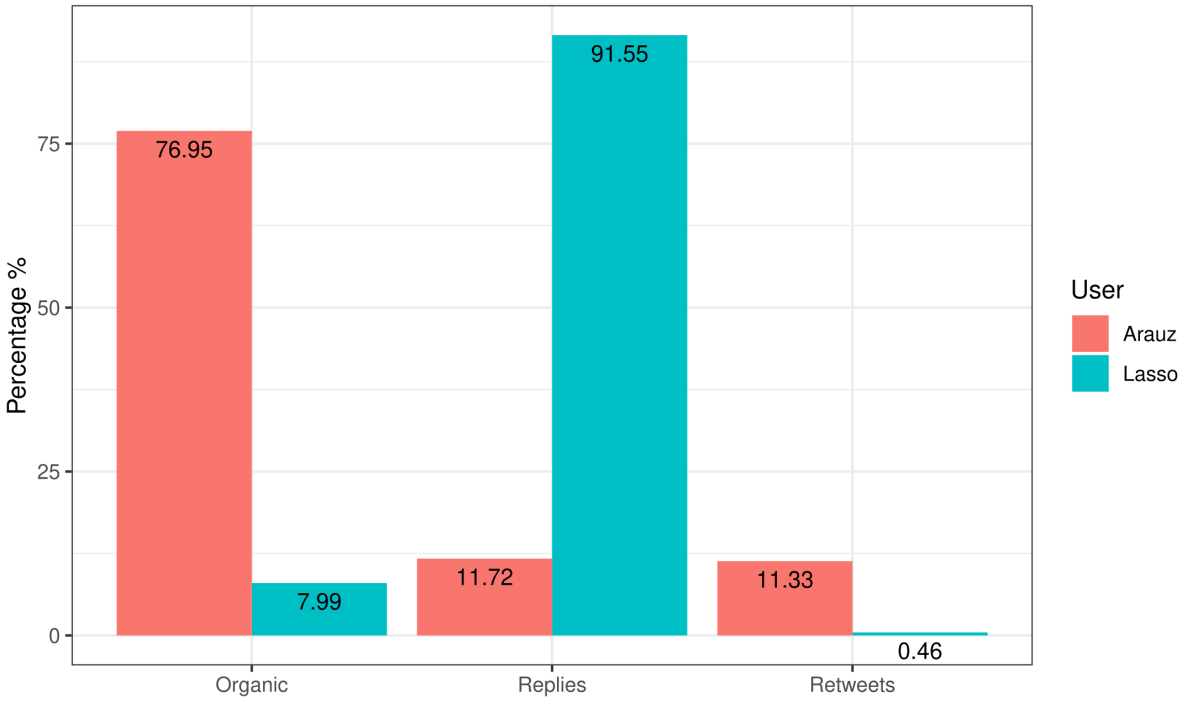

Figure 3.3 – The nature of each candidate's tweets.

Figure 3.4 illustrates the frequency of tweets from both candidates throughout the election campaign. A notable observation emerges, indicating a significant disparity in the tweeting patterns of the two candidates. Specifically, candidate Lasso has maintained a markedly higher tweet rate, with approximately eight times as many tweets as candidate Arauz. This discrepancy underscores the distinct emphasis candidate Lasso placed on leveraging the Twitter platform for interaction with users.

The discernible difference in tweet frequency between the candidates suggests varied approaches to online communication and user engagement. Candidate Lasso's more prolific tweeting indicates a concerted effort to maintain an active and continuous presence on Twitter, signaling an intentional strategy to connect with and inform the audience throughout the election campaign. This aspect of social media activity can play a pivotal role in shaping public perception and fostering direct engagement between political candidates and the electorate.

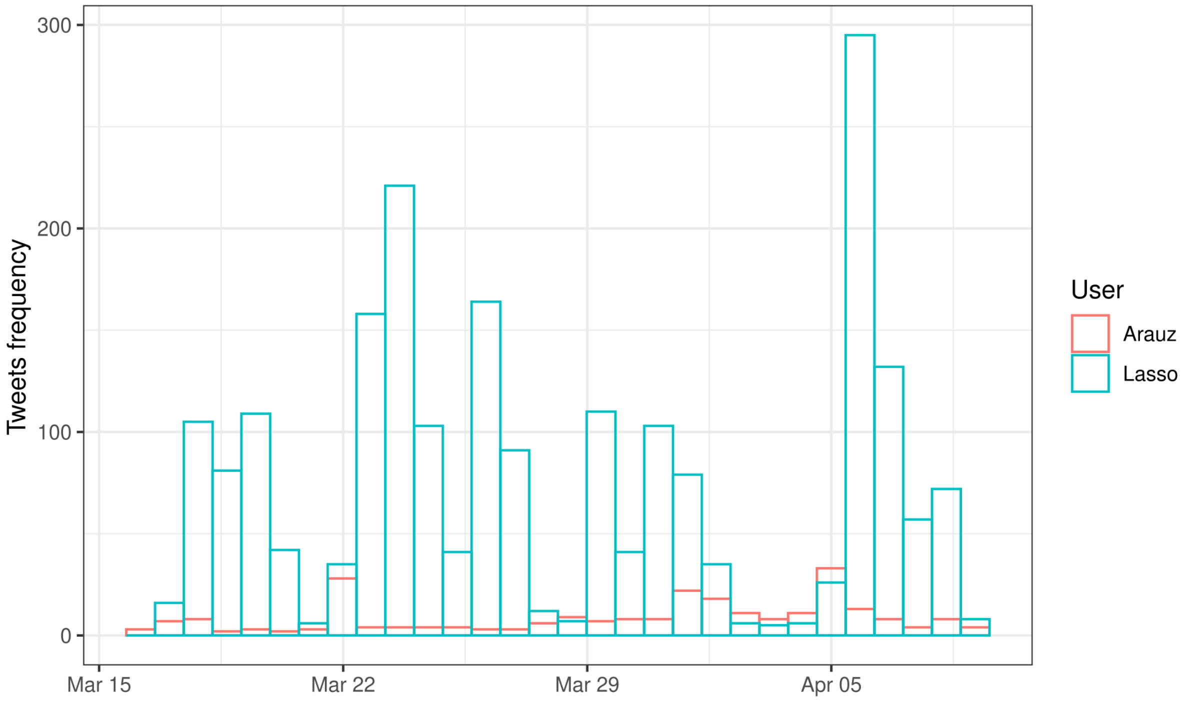

Figure 3.4 – Tweet frequency for every candidate.

After presenting an overview of both candidates' tweet sources, types, and frequencies, the subsequent focus shifts to a detailed analysis of the context within each candidate's tweets. In Figure 3.5, a comparative frequency analysis highlights the most common words used by each candidate. Words positioned close to the red line indicate roughly equal usage by both candidates, while those diverging from the line are employed more frequently by one candidate over the other.

Notably, both candidates share the use of common words such as "jóvenes" (young), "país" (country), and "compromiso" (commitment), typical in presidential discourse. However, candidate Arauz exhibits a more diverse vocabulary in his tweets, aligning with the expected outcome given the organic nature of 76.95% of his tweets. Conversely, candidate Lasso prominently features the words "vamos" (let's go) and "gracias" (thanks) with a higher frequency. This pattern aligns with the context of reply tweets, constituting 91.55% of candidate Lasso's tweet composition. The nuanced exploration of word frequencies provides insights into each candidate's linguistic choices, shedding light on their communication styles and strategic emphasis within the Twitter-sphere.

The next step involved the creation of a list containing tokenized words, facilitating the analysis of word frequency within the databases of both candidates. Subsequently, Figure 3.6 provides insights into the word frequency related to the trending hashtag #EncontremonosParaLograrlo from candidate Guillermo Lasso. This visual representation reveals the significant prevalence of this hashtag in the candidate's tweets.

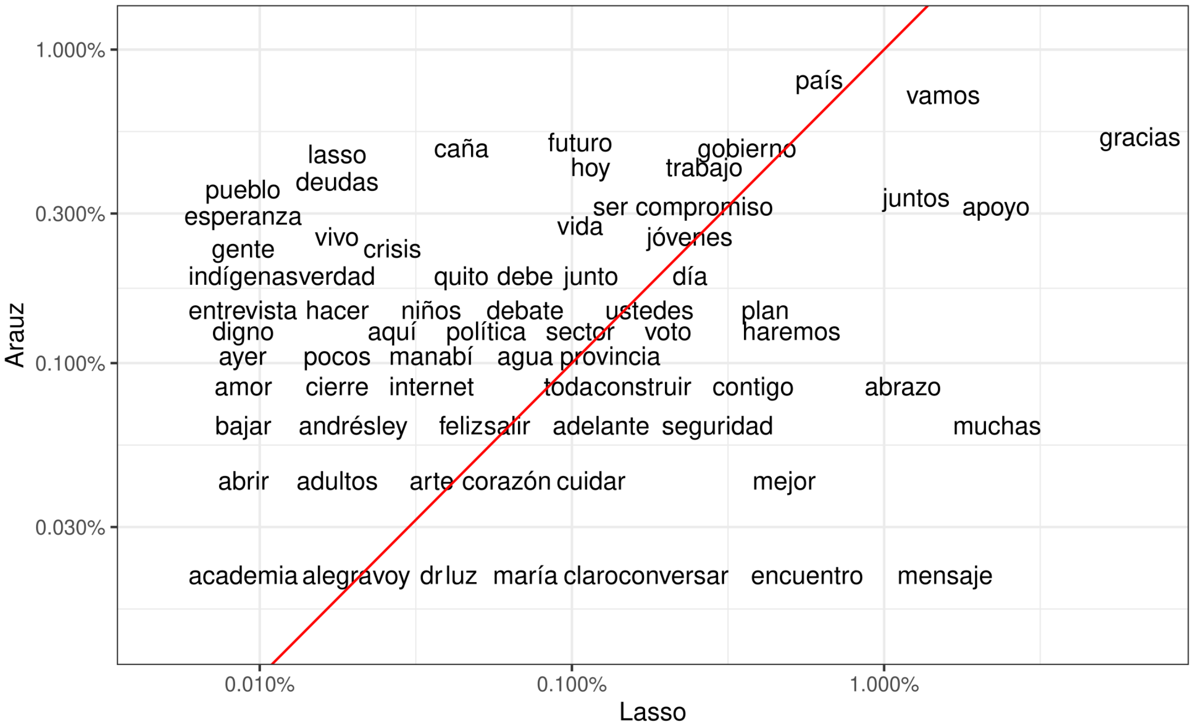

Figure 3.5 – Comparison of the terms used by each contender most frequently in their tweets.

Within Figure 3.6, it becomes apparent that the tweets associated with the hashtag frequently reference words such as "gobierno" (government), "progreso" (progress), "seguridad" (safety), "empleo" (employment), and others commonly employed in presidential proposals. This observation underscores the thematic focus of the tweets, aligning with key policy areas and indicative of the candidate's strategic emphasis on these topics within the context of the hashtag. The sequential analysis allows for a comprehensive understanding of the tokenized word frequency and sheds light on the specific themes dominating candidate Lasso's campaign discourse.

In Figure 3.7, the word cloud depicts the words with the highest frequency in tweets linked to the presidential candidate Andrés Arauz. An intriguing observation emerges as the most prominent word is not the associated hashtag trend but rather the word "trabajo" (work). Upon a closer examination of tweets featuring this word, it becomes evident that many of them allude to the arduous efforts undertaken over a span of 20 months. These efforts were aimed at fortifying the political movement and securing a position in the electoral second round. This becomes especially noteworthy given that candidate Andrés Arauz entered the political arena as a relatively unknown figure, participating in an election for the first time. The prominence of the word "trabajo" highlights not only a thematic focus on hard work but also provides contextual insight into the candidate's journey, emphasizing the efforts and dedication invested in reaching the electoral second round amid initial unfamiliarity.

Figure 3.6 – Word cloud for Guillermo Lasso, the contender, at #EncontremonosParaLograrlo.

Figure 3.7 – Word cloud of candidate Andrés Arauz for #ContigoConTodosAhora.

The distribution graphs showing the results of three different sentiment analysis techniques applied to the tweets are displayed in the following figures. Notably, tweets were primarily classified as negative or neutral using the Spanish sentiment analysis library *spanish_sentiment* (shown in Figure 3.8). On the other hand, tweets with neutral polarity were closely followed by a considerable number of tweets classified as positive by the TextBlob library (shown in Figure 3.9). On the other hand, the Vader library (shown in Figure 3.10) categorized most tweets as positive.

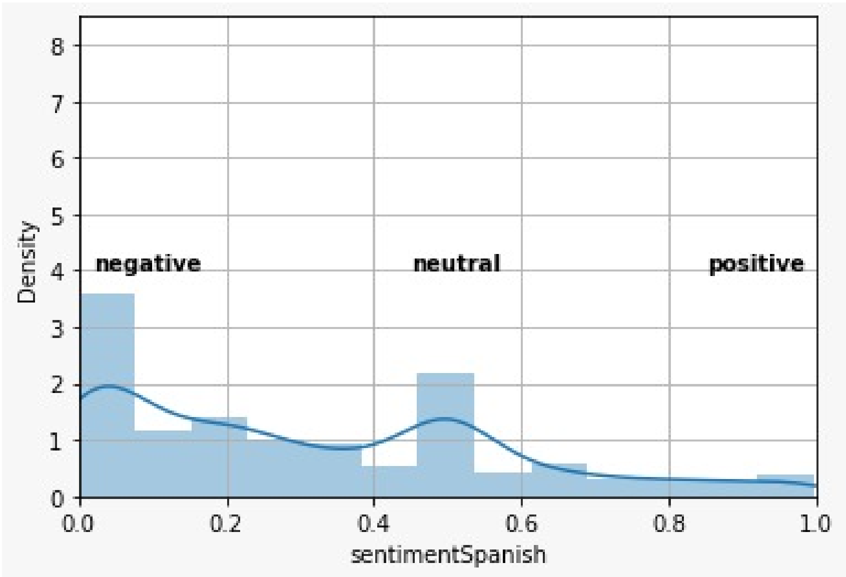

Figure 3.8 – Sentiment analysis of tweets gathered for Guillermo Lasso's campaign hashtag #EncontremonosParaLograrlo. (a) sentiment_spanish.

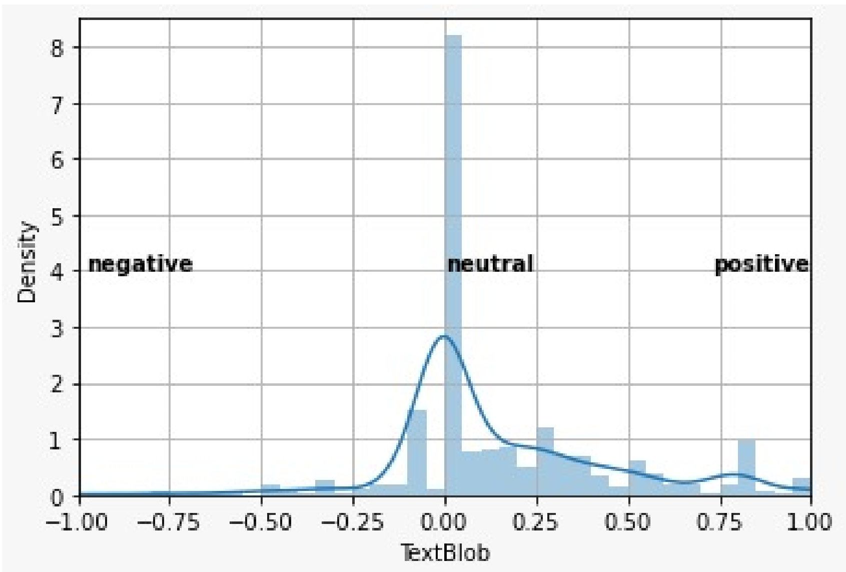

Figure 3.9 – Sentiment analysis of tweets gathered for Guillermo Lasso's campaign hashtag #EncontremonosParaLograrlo. (b) TextBlob.

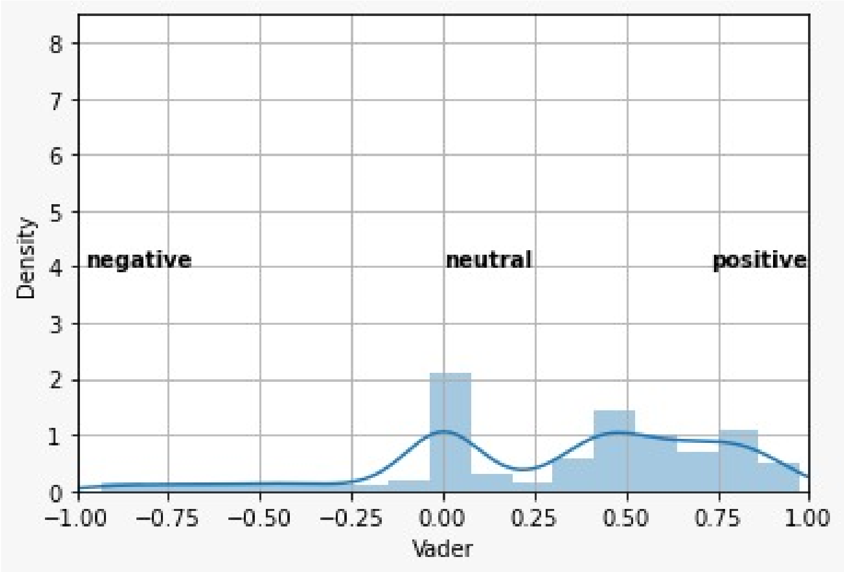

Figure 3.10 – Sentiment analysis of tweets gathered for Guillermo Lasso's campaign hashtag #EncontremonosParaLograrlo (c) Vader.

Moving on to Figure 3.11, a comparative analysis of the three sentiment analysis libraries is presented concerning the tweets collected from candidate Lasso. Notably, both TextBlob and Vader libraries consistently demonstrated effective classification of a substantial proportion of tweets with positive polarity. This comparison sheds light on the varying tendencies of sentiment classification across the employed libraries, emphasizing the nuanced outcomes and potential considerations for each approach in the context of analyzing tweets.

Figure 3.11 – The candidate Guillermo Lasso's sentiment was analyzed using *spanish_sentiment*, *TextBlob*, and *Vader*.

In the following Figures, a distinct pattern emerges, revealing a notable inclination of both the TextBlob library (refer to Figure 3.13) and the Vader library (refer to Figure 3.14) to classify tweets within the range from 0 to 1. This range predominantly consists of tweets classified as either neutral or positive, indicating that the majority of tweets fall into these sentiment categories. Conversely, the *spanish_sentiment* library (depicted in Figure 3.12) exhibits a contrasting trend, classifying a significant portion of tweets as negative, followed by those labeled as neutral.

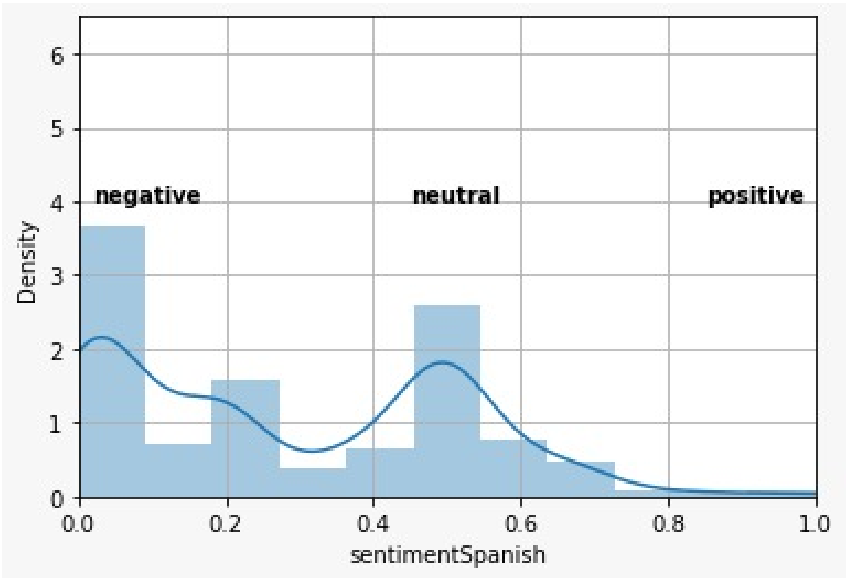

Figure 3.12 – Sentiment analysis of tweets gathered for Andrés Arauz's #ContigoConTodosAhora trend. (a) sentiment_spanish.

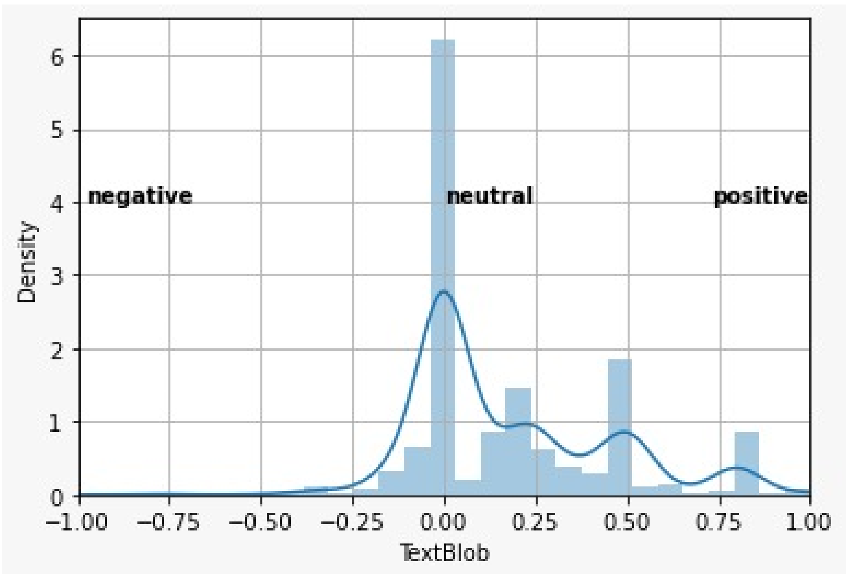

Figure 3.13 – Sentiment analysis of tweets gathered for Andrés Arauz's #ContigoConTodosAhora trend. (b) TextBlob.

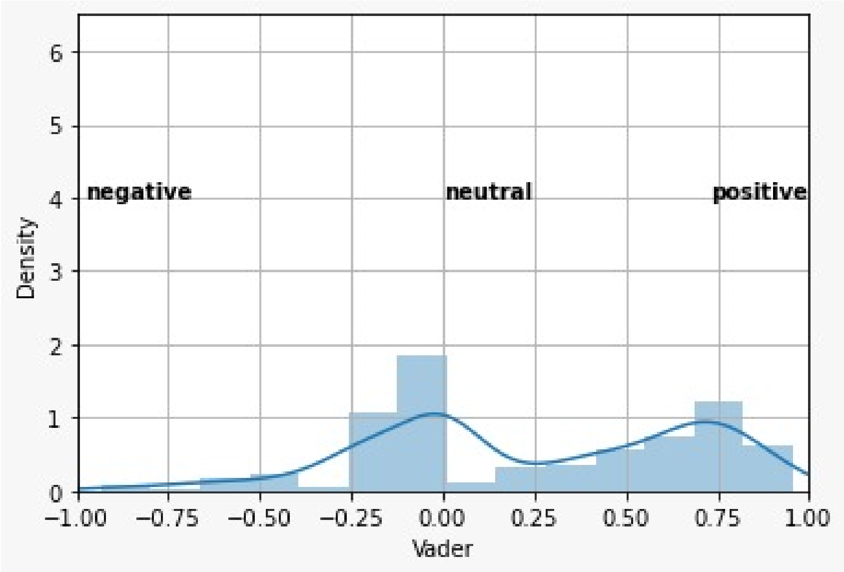

Figure 3.14 – Sentiment analysis of tweets gathered for Andrés Arauz's #ContigoConTodosAhora trend. (c) Vader.

Figure 3.15 provides an overarching view of how each sentiment analysis library categorized tweets related to candidate Andrés Arauz. Notably, the *spanish_sentiment* classifier demonstrates a prevalent tendency toward negative sentiment classification. In stark contrast, both the TextBlob and Vader libraries exhibit a prevailing pattern of classifying a majority of tweets with positive polarity. This comparative analysis unveils the diverse tendencies of sentiment classification within the context of tweets associated with candidate Andrés Arauz across the employed libraries, emphasizing the nuanced outcomes and potential considerations for each sentiment analysis approach.

Figure 3.15 – Sentiment analysis of candidate Andrés Arauz using *spanish_sentiment*, *TextBlob*, and *Vader*.

Figures 3.11 and 3.15 clearly show how tweet translations impact results, underscoring significant discrepancies in the final sentiment classifications. To enhance accuracy and ensure consistent outcomes in sentiment classification between Spanish and English, it is imperative to utilize Large Language Models (LLMs). Furthermore, another way will be to build a big dataset centered on political topics, which will be leveraged to train a sentiment analysis package from the ground up, ensuring better performance.

4 Analysis of CNN-LSTM-Based Approaches for Human Activity Recognition

The topic of Human Activity Recognition (HAR) is concerned with creating algorithms that can understand and interpret a wide range of human behaviors. These actions, which include walking, running, jumping, and gestures, are usually recorded in the form of movies or image sequences (SHUVO *et al.*, 2020). The importance of HAR is seen in its wide range of applications, which include surveillance, human-computer interaction, ambient supported living, health monitoring, treatment activities, and sports.

HAR is classified into two primary categories: vision-based HAR and sensor-based HAR, depending on the type of data it processes (DANG *et al.*, 2020). A vision-based approach includes an analysis of camera data provided as images or videos (FEICHTENHOFER *et al.*, 2016). On the other hand, a sensor-based system uses sensors like magnetometers, gyroscopes, radars, and accelerometers to analyze data in the form of time series (ZHENG; ZHANG, 2021). Notably, accelerometers are the most commonly used sensors in HAR because of their affordability, mobility, and small size.

As depicted in Figure 4.1, a typical HAR system takes a video as input, wherein the ongoing action is identified through labeled annotations. Subsequently, a dedicated model is responsible for establishing relationships and making predictions (LATHA; SHEELA, 2019). Numerous datasets, such as UCF101, HMDB51, Kinetics, ActivityNet, and NTU RGB+D, play a pivotal role in HAR research by providing benchmarks for evaluating the performance of various algorithms and techniques (PAREEK; THAKKAR, 2021)[12].

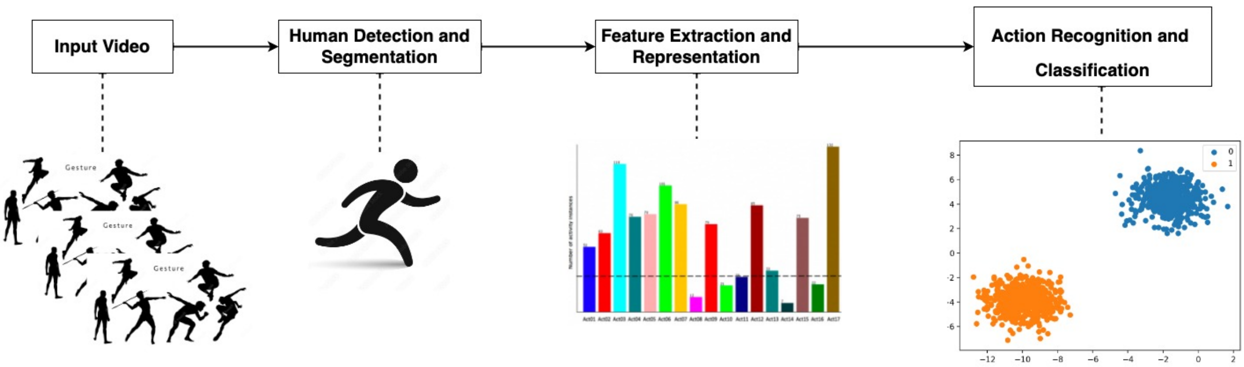

Figure 4.1 – A typical Human Activity Recognition System

The high applicability of HAR has positioned it as a significant subject of study within the academic community, contributing to the evolution of complex and sophisti-

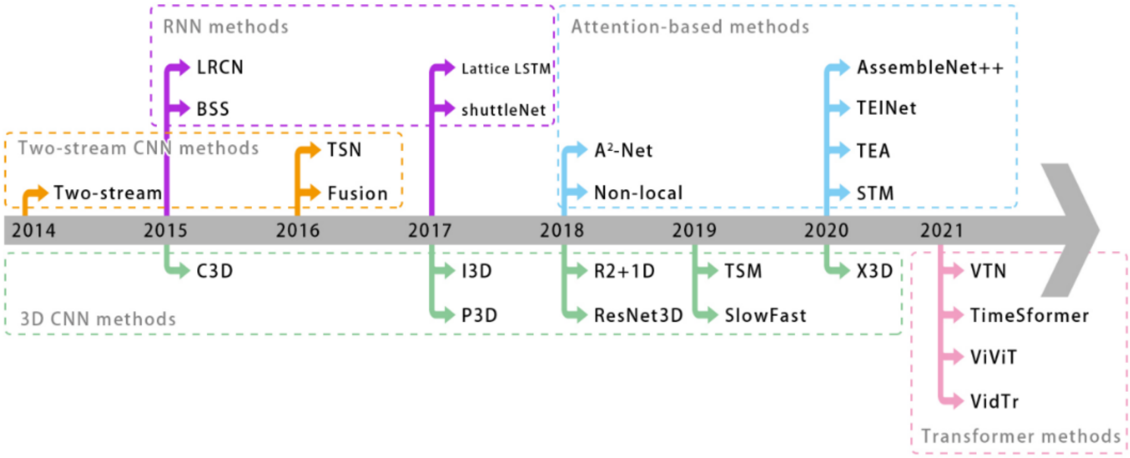

Figure 4.2 – Some representative methods in video human action recognition by category (ZHANG *et al.*, 2021).

cated algorithms over the years. Figure 4.2 illustrates diverse HAR approaches, featuring techniques based on Long-Term Short Memory (LSTM) and Convolutional Neural Networks (CNNs). Noteworthy recent works in human activity identification, employing these advanced techniques, are detailed in this comprehensive literature review. The field continues to advance, driven by ongoing research and the collaborative efforts of scholars, fostering the development of innovative algorithms and pushing the boundaries of HAR applications.

4.1 Methods applied on HAR

Figure 4.2 presents a chronological trend that highlights significant milestones in HAR methods. This timeline includes important techniques including CNN networks, RNNs, attention-based CNNs, 3D CNNs, and the new transformer-based trends (ZHANG *et al.*, 2021). Every one of these approaches has been rigorously tested and incorporates sophisticated and strong strategies to increase efficacy. The next sections will provide a thorough overview of these approaches' evolution and contributions to the area of HAR by delving into the explanations of each methodology and illuminating the creative strategies and advancements linked with each.

4.1.1 LSTM and CNN

Among recurrent neural networks, the Long Short-Term Memory (LSTM) is distinguished by its remarkable capacity to process sequential input. Since activity sequences may be thought of as time series data obtained from sensors, LSTM is especially useful for identifying patterns in human activity (DAI *et al.*, 2020). Conversely, Convolutional Neural Networks (CNNs), which were originally designed for image identification tasks, have demonstrated impressive performance in the field of recognising human activities by processing sensor data as though it were visual images. This modification highlights CNNs' adaptability and demonstrates how they can be used for purposes other than those for which they were intended.

In a pioneering experiment referenced in (FEICHTENHOFER *et al.*, 2016), researchers applied LSTM for HAR. As shown in Figure 4.3, they created a multi-layer LSTM model to identify routine actions based on information gathered from electronic device sensors. With an accuracy of 91.8% on a dataset with six different activities, their model demonstrated how well LSTM captures temporal patterns.

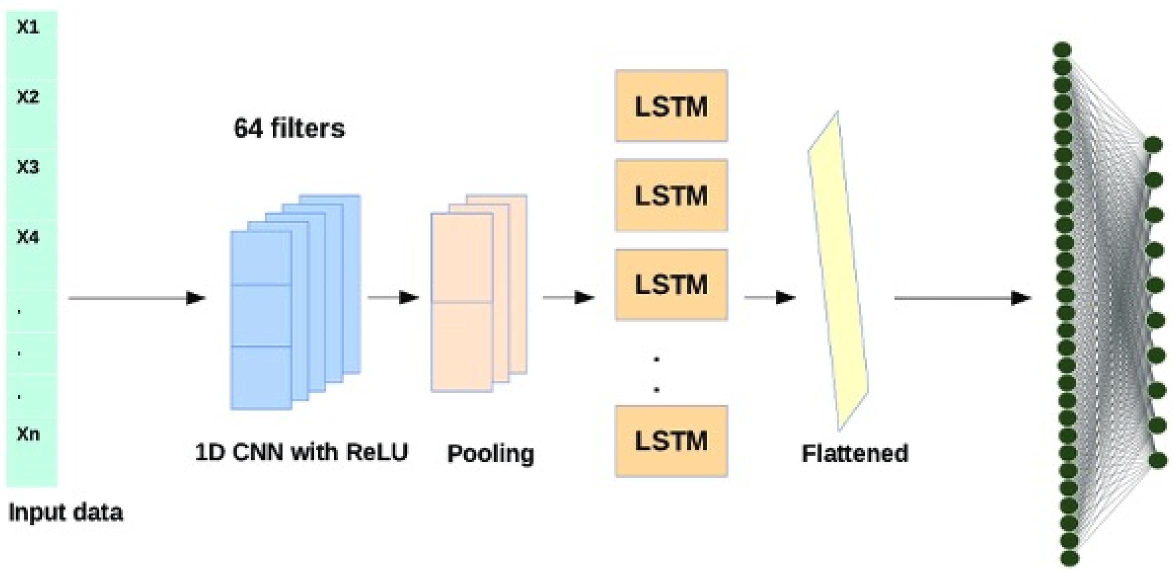

Figure 4.3 – Illustration of 1D CNN and LSTM for HAR.

In a more recent publication detailed in (HAMMERLA *et al.*, 2016), the same authors extended their exploration by incorporating both LSTM and CNN for HAR. They created a two-stream architecture that combines LSTM and CNN to understand sensor input fully. Whereas the CNN stream took sensor data and derived spatial information, the LSTM stream concentrated on capturing temporal changes in activity sequences. These two streams were then smoothly combined in a later fully connected layer, yielding an accuracy of 89.1% on a dataset of six activities. This performance is in line with state-of-the-art methods, confirming the effectiveness of the CNN and LSTM model combination in improving the ability to recognize human activities.

In (ORDÓÑEZ; ROGGEN, 2016), a unique method combining CNN and LSTM approaches was presented. This methodology used a two-step procedure to identify human activity. First, features were retrieved from the sensor data using a CNN. These features were then used as input into an LSTM model to do classification. Impressively, this integrated technique obtained a remarkable accuracy of 93.9% on a dataset including eight activities, surpassing the performance of most previous methods.

As noted in (ZHANG *et al.*, 2019), the same author presented an enhanced framework for human activity recognition in a more recent work. This framework seamlessly integrated deep CNNs with bidirectional LSTM (BiLSTM). By combining these two potent methods, it was possible to take advantage of CNNs' spatial feature extraction skills and BiLSTM's sequential modeling expertise, offering a complete and practical solution for correctly identifying a variety of human activities.

4.1.2 Skeleton-Based ST-GCN for HAR

Because skeleton data represents posture structure in a view-invariant manner, its integration has gained popularity in the field of HAR. Human skeletal data presented in graph form offers a more reliable and succinct depiction of human movements than RGB video data, which is subject to various factors such as perspective variations, occlusions, cluttered backgrounds, differing poses, lighting conditions, and attire (WANG *et al.*, 2022). It is possible to obtain skeletal data by using cameras or techniques intended for human posture prediction (DAI *et al.*, 2020).

Skeletal data is important because it provides a human activity representation that is less influenced by outside factors. This is especially useful in situations where environmental factors can have a big impact on the recognition accuracy. HAR systems using skeleton data can recognize human activities more reliably and accurately by focusing on the skeletal structure, which is more stable in a variety of contexts. This increases the overall effectiveness and robustness of the recognition process. Its application in real-world settings is further enhanced by the versatility of skeletal data acquired using cameras or predictive posture methods, which ensures adaptability to varied data collection setups and scenarios.

The authors of a research study described in (SHI *et al.*, 2019) present a novel method for video-based human action identification using skeleton data called the two-stream adaptive graph convolutional network (2S-AGCN). This novel network is made to examine first- and second-order information that is present in the skeleton. Joint positions are encoded with first-order information, which offers insights into the spatial organization of important body points. In addition, second-order information contributes to a more thorough comprehension of the subject's movement dynamics by capturing important data like the lengths and orientations of the bones in the human skeleton.

The 2S-AGCN's emphasis on skeletal data, which provides a view-invariant description of human pose structure, is one of its main advantages. In contrast to image-based methods that are vulnerable to issues such as brightness fluctuations, background motion, color discrepancies, and various individual traits, the utilization of 3D models in skeleton data enables flexibility in a broad spectrum of situations once they are recognized. In practical applications, this flexibility is essential since it increases the network's resilience and guarantees accurate detection of human activity even in difficult environmental circumstances. The suggested 2S-AGCN is a viable method for improving the precision and adaptability of video-based human action detection systems since it incorporates both first- and second-order information, highlighting its capacity to extract minute features from skeleton data.

Because of its primary goal of giving the same label to the same actions regardless of the person performing them or the contextual variations in situations or styles, skeleton graph integration stands out as a very promising strategy in HAR. There has been a noticeable upsurge in the use of Graph Neural Networks (GNNs) recently, with Graph Convolution Networks (GCNs) taking the lead and blending in nicely with the skeleton graph framework. The Skeleton GCN (ST-GCN), a ground-breaking model first presented in (SHI *et al.*, 2019), is a crucial turning point in this trajectory. Figure 4.4 illustrates its architectural framework.

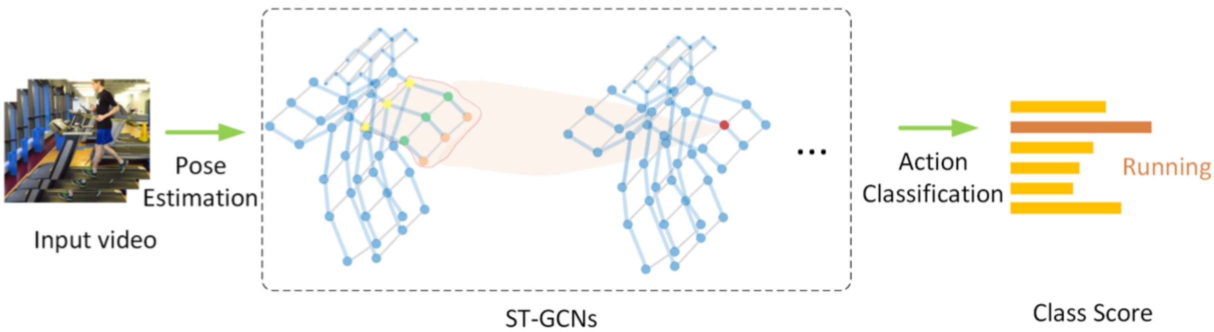

Figure 4.4 – Skeleton Graph Neural Network (ST-GNNs)

The skeleton graph's attraction is its ability to capture the universal aspects of human pose structure, guaranteeing that HAR systems retain consistency in action detection among different actors and scenarios. The emergence of GNNs, particularly GCNs, has given rise to a powerful toolkit for efficiently processing data inside these skeleton graphs. With its unique architecture, the ST-GCN represents a significant breakthrough, demonstrating how graph-based techniques may greatly improve the accuracy and flexibility of HAR systems.

The architecture of the ST-GCN is specifically designed to take advantage of the intrinsic connections found in the skeleton graph, as seen in Figure 4.4. This makes it possible for the model to identify complex patterns associated with human movement, leading to a more sophisticated comprehension of activities. The smooth incorporation of GNNs into the skeleton graph serves to both support and expand upon the goal of consistent action labeling, allowing for enhanced context-aware comprehension in a variety of dynamic circumstances. The architectural model of the ST-GCN highlights the revolutionary possibilities resulting from the combination of skeleton graphs and GNNs and acts as a visual testimony to the changing landscape of HAR methods.

4.1.3 Support Vector Machine

The Support Vector Machine (SVM) is a machine learning algorithm that discovers the optimal hyperplane for splitting input data. It was first developed for binary classification issues. Notably, SVM has several advantages over other machine learning techniques, including:

1. **High-Dimensional Data Handling:** SVM is particularly good at managing data that is located in high-dimensional spaces. Its versatility across a wide range of applications is facilitated by this characteristic, which makes it especially successful in circumstances where datasets involve a number of features.

2. **Memory Efficiency:** Because SVM may function with subsets of training data points, it has an efficient memory consumption characteristic. When working with large datasets, this feature becomes extremely helpful as it enables SVM to manage memory resources wisely without sacrificing performance.

3. **High Feature Dimensionality:** SVM's capacity to function in scenarios where the number of features (dimensions) exceeds the number of data samples is another significant strength. This is an essential property that allows SVM to function well in situations involving intricate, high-dimensional feature spaces, which makes it appropriate for a wide range of real-world uses.

SVM is widely applicable and effective in a variety of machine learning tasks primarily due to its skills in managing high-dimensional data, memory efficiency, and its capacity to function in settings with high feature dimensionality. Because of these qualities, SVM is a useful tool when applying classical algorithms, which may face difficulties due to the volume and complexity of the data.

During training, SVM runs calculations to create hyperplanes that identify differences between different classes or labels in the training set. The "one-vs-all" and "one-vs-one" techniques are the two main ways that SVM can be expanded to handle the complexity of multi-class classification issues.

- SVM concurrently takes into account all classes within a single optimization problem when using the "one-vs-all" approach. However, this method can be computationally intensive since each class needs a separate SVM to be created.
- The "one-vs-one" technique, on the other hand, adopts a different approach by building and combining binary classifiers. These classifiers together serve as a multi-class classifier, not only elevating classification accuracy but also mitigating computing complexity, as proven in research such as (SHUVO *et al.*, 2020).

SVM, which was originally designed for binary classification, has a number of benefits. Its versatility is demonstrated by its excellent expansions to handle multi-class classification complexity using different approaches, such the useful "one-vs-all" method. Because of its adaptability, SVM is positioned as a reliable and powerful machine learning technique that can accurately and effectively handle a wide range of classification problems.

4.2 Techniques for HAR methods

4.2.1 Pooling Layer

The pooling layer is a crucial part whether it is utilized for global maximum pooling, global average pooling, global average pooling, or maximum pooling. In a study (KARPATHY *et al.*, 2014), the authors combined one global average pooling layer and one maximum pooling layer. The main purpose of pooling is to simplify the downsampling procedure. More precisely, maximal pooling dramatically reduces the dimensionality of the output units originating from the convolutional layer. By carefully selecting the maximum values from each feature space, this reduction is accomplished. Maximum pooling reduces computational load and reduces the possibility of overfitting by doing this. This methodical approach to selection aids in preserving crucial details while skillfully controlling the model's intricacy, which enhances generalization performance.

4.2.2 VGG16

In order to extract features from individual video frames, VGG16 must be applied. As seen in (FEICHTENHOFER *et al.*, 2016), the sequence of frame features that is obtained is then fed into LSTM recurrent networks in order to do classification. In this procedure, an LSTM neural network performs the classification task after a neural network is used to extract the video's intrinsic attributes. Recurrent neural networks (RNNs) are a particular subtype of LSTMs. It is important to remember that neural networks are artificial intelligence systems. Long short-term memory banks (LSTMs) are particularly well-suited for tasks like video classification that require modeling long-range and temporal links within data sequences because of their unique capacity to store and use information for extended periods of time. One of the main reasons LSTMs are so effective at handling the temporal dynamics seen in video data is that they have an innate capacity to store information for extended periods of time.

4.2.3 ConvLSTM

With convolution operations built into its architecture, the ConvLSTM cell is a modified version of the LSTM network. It basically combines the best aspects of both convolutional and LSTM layers, giving it the capacity to analyze temporal correlations and identify spatial characteristics in input data. The ConvLSTM is especially useful for video classification because of its distinctive design, which makes it capable of effectively capturing both the temporal relationships between frames and the spatial properties inside individual frames. Convolutional structures are added to the ConvLSTM to improve its recognition and processing of spatial data. This makes the model much more effective at tasks requiring a comprehensive comprehension of both spatial and temporal dimensions, like video analysis, as demonstrated in Figure 4.5 and highlighted in (SHI *et al.*, 2015).

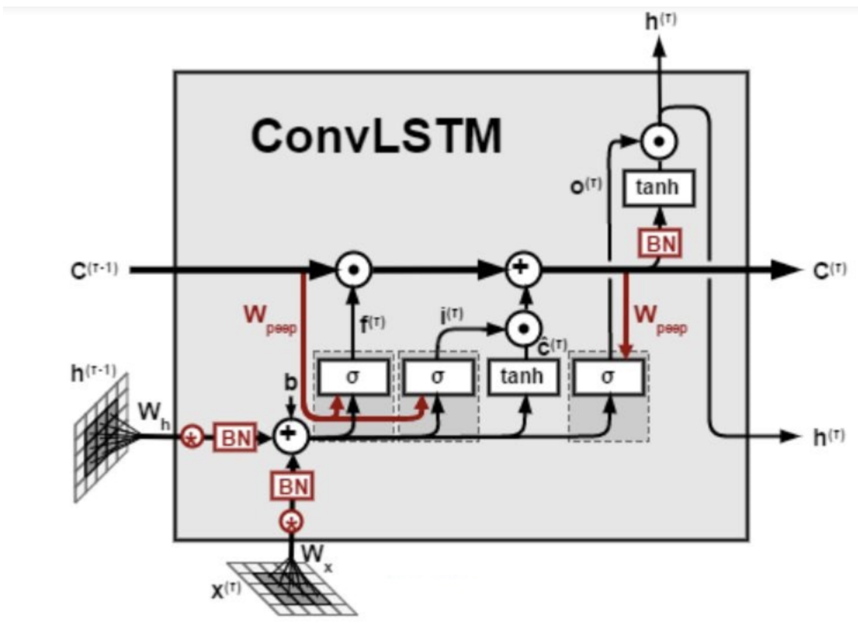

Figure 4.5 – Illustration of a ConvLSTM Structure

The width, height, and number of channels of 3D input data can all be handled by the ConvLSTM. A typical LSTM, on the other hand, is only able to process input in 1D, which makes it inappropriate for modeling spatiotemporal data independently. This constraint results from the inbuilt incapacity of an LSTM to represent the spatial dimensions present in 2D or 3D data structures.

To explain further, the ConvLSTM's capacity to handle information in both spatial and temporal dimensions becomes critical when working with data sequences, such as those found in spatiotemporal contexts like video frames. This flexibility guarantees that the model can identify complex patterns in the data, taking into account both the spatial arrangement and the frame-by-frame ordering.

The model can be expressed mathematically through the following equation (SHI *et al.*, 2015):

$$h_t, c_t = (x_t h_{t-1}, h_{t-1}) \tag{4.1}$$

This equation succinctly captures the intricate transformation and information flow within the ConvLSTM, illustrating its efficacy in handling the intricate nature of spatiotemporal data. In this context, the equation's components are x_t represent the input tensor at time step t, h_{t-1} and c_{t-1} denotes the hidden state and cell state of the ConvLSTM at the previous time step $t-1$, h_t and c_t are the hidden state and cell state of the ConvLSTM at the current time step t.

In the ConvLSTM paradigm, these variables essentially capture the information's temporal evolution. ConvLSTM architecture consists of four essential parts:

- The input gate regulates the amount of the input tensor that is contributed to the cell state.
- The forget gate regulates the amount of the prior cell state that is kept.
- Cell gate calculates the new cell state value depending on the input tensor and the previous cell state.
- The output gate regulates the amount of the cell state that is utilized in the output computation.

As explained in more detail in (WANG *et al.*, 2018), these gates collectively enhance the model's capacity to identify and record significant patterns in both spatial and temporal dimensions.

4.2.4 Sequence Modelling using Long Short-Term Memory

Previous studies have shown that a particular recurrent neural network (RNN) architecture called Long Short-Term Memory (LSTM) is stable and effective at modeling long-range dependencies, especially in general-purpose sequence modeling. One of the main innovations of LSTM is its memory cell c_t, which serves as an effective state information accumulator. Self-parameterized controlling gates that are in charge of reading from, writing to, and clearing the memory cell make this possible.

Upon the arrival of a new input, its data is assimilated into the cell if the input gate is activated. Moreover, if the forget gate f_t is engaged, the previous cell state c_{t-1} may undergo "forgetting" during this process. Subsequently, the output gate regulates whether the most recent cell output c_t is propagated to the final state h_t (SHI *et al.*, 2015). Leveraging memory cells and gates to govern information flow offers the advantage of confining gradients within the cell, a concept known as continuous error carousels, thus mitigating the risk of rapid vanishing (SHI *et al.*, 2015). The essential equations are presented below, with the symbol '$\circ$' denoting the Hadamard product:

$$
\begin{aligned}
i_t &= \sigma\left(W_{xi}x_t + W_{hi}h_{t-1} + W_{ci}c_{t-1} + b_i\right)\\
f_t &= \sigma\left(W_{xf}x_i + W_{hf}h_{t-1} + W_{cf}c_{t-1} + b_f\right)\\
c_t &= f_t \circ c_{t-1} + i_t \circ \tan_h\left(W_{xc}x_t + W_{hc}h_{t-1} + b_c\right)\\
o_t &= \sigma\left(W_{xo}x_t + W_{ho}h_{t-1} + W_{co} \circ c_t + b_o\right)\\
h_t &= o_t \circ \tan_h\left(c_t\right)
\end{aligned} \tag{4.2}
$$

i_t, f_t, and o_t are the input, forget, and output gates at time step t, respectively. W_i, W_f, W_c, and W_o are the convolutional filters for each of the gates. b_i, b_f, b_c, and b_o are the bias terms for each of the gates.

4.2.5 Long-Term Recurrent Convolutional Networks (LRCN)

The LRCN technique seamlessly integrates Convolutional and LSTM layers within a unified model. Alternatively, a comparable strategy involves employing a CNN model and an LSTM model independently, as depicted in Figure 4.6. This distinct approach entails training the CNN to extract spatial features from frames, with these features subsequently fed into LSTM layers at each time step for temporal sequence modeling.

In this dual-model configuration, the Convolutional layers play a pivotal role in extracting spatial features, emphasizing the spatial characteristics within individual frames. The extracted spatial features are then seamlessly integrated into the LSTM lay-

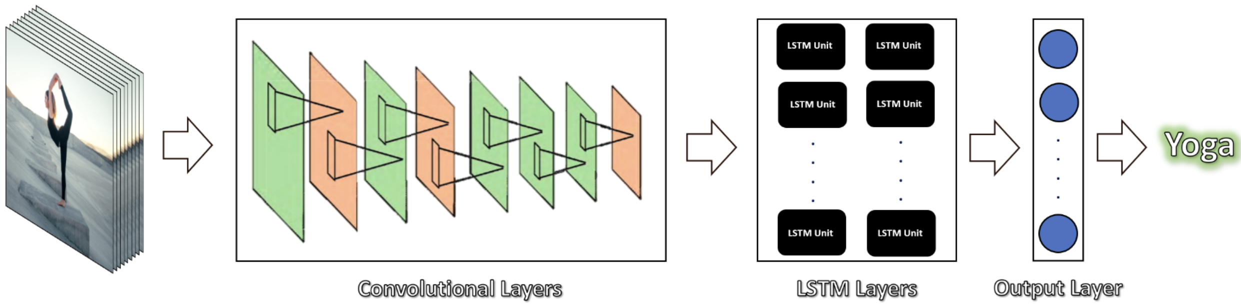

Figure 4.6 – LRCN Architecture (DONAHUE *et al.*, 2015)

ers, allowing the model to comprehend temporal dependencies across different frames. The advantage of this approach lies in its end-to-end training process, enabling the network to learn spatio-temporal features directly. This end-to-end learning contributes to the development of a robust model, as discussed in (DONAHUE *et al.*, 2015). The integration of spatial and temporal information ensures a comprehensive understanding of the dynamic nature of data sequences, enhancing the model's performance in tasks such as video analysis or action recognition.

4.3 Methods Comparison

In Table 4.1, a comprehensive comparison of the methods discussed in this section is provided. Notably, three CNN-based approaches—Context Stream, VGG-M-2048, and CNN-Based ResNet 50—are analyzed, each leveraging CNNs for feature extraction. However, their distinctions lie in the specific architecture of the CNN employed.

Table 4.1 – Efficiency of CNN-LSTM as compared to other methods.

Approach	**Model**	**Dataset**	**Accuracy(%)**	Published year
CNN Based	Context-Stream (KARPATHY *et al.*, 2014)	UFC	63.3%	2014
CNN Based	VGG-M-2048 (FEICHTENHOFER *et al.*, 2016)	UFC	92.5%	2016
CNN Based	ResNet 50 (ZHENG; ZHANG, 2021)	UCF	94.2%	2016
Hybrid Based	SVM (SHUVO *et al.*, 2020)	UCI-HAR	91.15%	2017
RNN Based	ConvNet+LSTM (NAEEM *et al.*, 2021)	UCF	89.2%	2018
Skeleton Based	2S-EGCN (WANG *et al.*, 2022)	NTU-RGB+D	95.5%	2022
RNN Based	GoogleLeNet (YU *et al.*, 2019)	UCF	88.5%	2020
RNN Based	LSTM (DAI *et al.*, 2020)	UCF	89.11%	2020
Combined Based	C3D+SVM (LI *et al.*, 2018)	UCF	89.0%	2021

The Context Stream approach, as outlined in (KARPATHY *et al.*, 2014), adopts a unique strategy by utilizing separate streams to process spatial and temporal information. This design enables the incorporation of both spatial and temporal features in video analysis, contributing to enhanced accuracy in action recognition. Nevertheless, it's important to note that this approach demands a substantial amount of labeled data for effective training and incurs significant computational expenses.

Conversely, deep CNN architectures aimed at learning high-level features include VGG-M-2048 and ResNet-50. On the UCF dataset, ResNet-50 yields the greatest accuracy of the three approaches, with 94.2%; VGG-M-2048 follows with 92.5%, and Context Stream with 63.3%. ResNet-50's strong performance highlights how well it captures complex features for precise action recognition. Making an informed selection when choosing a method based on certain criteria and limits is made easier with this comprehensive grasp of the relative strengths and drawbacks of these CNN-based approaches.

Furthermore, the RNN-based ConvNet+LSTM and the hybrid-based SVM use different models for feature extraction and classification. The hybrid-based SVM blends SVM with handmade features, emphasizing a fusion approach. On the other hand, the ConvNet+LSTM, which is based on RNNs, utilizes both CNNs and LSTMs, exhibiting an advanced architecture for feature extraction. When comparing their UCF dataset results, the RNN-based ConvNet+LSTM outperforms the Hybrid-Based SVM in terms of accuracy. This better performance is explained by the complementary abilities of CNNs and LSTMs to capture temporal and spatial information, providing a more thorough comprehension of dynamic video sequences.

Although the Support Vector Machine (SVM) technique is widely used for human activity recognition due to its ease of use and simplicity, one of its limitations is its inability to efficiently collect temporal information. This flaw may lead to decreased accuracy, particularly on tasks that require temporal dynamics. The detailed comparison of different methods emphasizes how crucial it is to choose models according to the particular needs of the work at hand, taking into account elements like accuracy, complexity, and the type of temporal dependencies present in the data, as described in (SHUVO *et al.*, 2020).

The unique feature extraction technique of the Skeleton-Based 2S-EGCN method is achieved through the use of Graph Convolutional Networks (GCNs) that are specifically tailored for skeleton data. Interestingly, this approach achieves cutting edge results on the NTU-RGB+D dataset, a commonly used benchmark for 3D action detection. Because of its excellent accuracy in action identification tasks, the 2S-EGCN technique is unique in that it is particularly good at modeling the spatial and temporal aspects that are intrinsic in human skeletal actions. Its ability to adjust to differences in skeletal data between different people is an additional benefit that increases its robustness across various participants. It's important to remember that the 2S-EGCN's effectiveness has a price. To fully utilize the method, a significant amount of training data is needed, and it has quite high computational needs. Although the model is excellent at capturing subtle traits and accounting for individual variances, its resource-intensive nature needs to be taken into account in real-world applications, as (KARPATHY *et al.*, 2014) discusses.

While RNNs are used for feature extraction in all three approaches—RNN-Based GoogleLeNet, RNN-Based LSTM, and Combined-Based C3D+SVM—they differ in the kind of RNN used and how it is combined with other models. An LSTM layer is added to a modified version of the GoogleLeNet architecture in RNN-Based GoogleLeNet. RNN-Based LSTM, on the other hand, uses just Long Short-Term Memory (LSTM) networks to extract features. Conversely, Combined-Based C3D+SVM combines an SVM classifier with a 3D Convolutional Neural Network (C3D).

When it comes to applications like human activity identification, the LSTM technique's unique strength lies in its capacity to extract long-term dependencies from time series data. Because of its exceptional ability to tolerate noisy or missing data, LSTM enhances overall robustness in real-world applications. However, as mentioned in, it's important to consider the computational expense and the need for a sizable amount of LSTM training data. (FEICHTENHOFER *et al.*, 2016). Based on particular application needs and limits, this thorough comparison offers insightful information about the benefits and trade-offs of each method, assisting in the educated selection of an acceptable solution.

5 Human Activity Recognition Implementing CNN-LSTM

In this chapter, the goal is to build a classification model that can identify the particular human task that is being carried out. This project uses deep learning models that leverage the synergy between Long Short-Term Memory (LSTM) and Convolutional Neural Networks (CNN). This combination makes sense because of CNN's superior picture classification capabilities and LSTM's ability to handle sequential input.

The overarching structure of the proposed model is shown in Figure 5.1. Through the integration of CNN and Many to One LSTM, the model seeks to harness the optimal features of both methodologies. The core methodology involves segmenting the video into a series of frames. Subsequently, CNN is employed to extract visual features from these frames. These visual features are then input into the LSTM network, facilitating the prediction of the activity being performed. A pivotal aspect involves a thorough performance evaluation, comparing the proposed model against established techniques detailed in the existing literature.

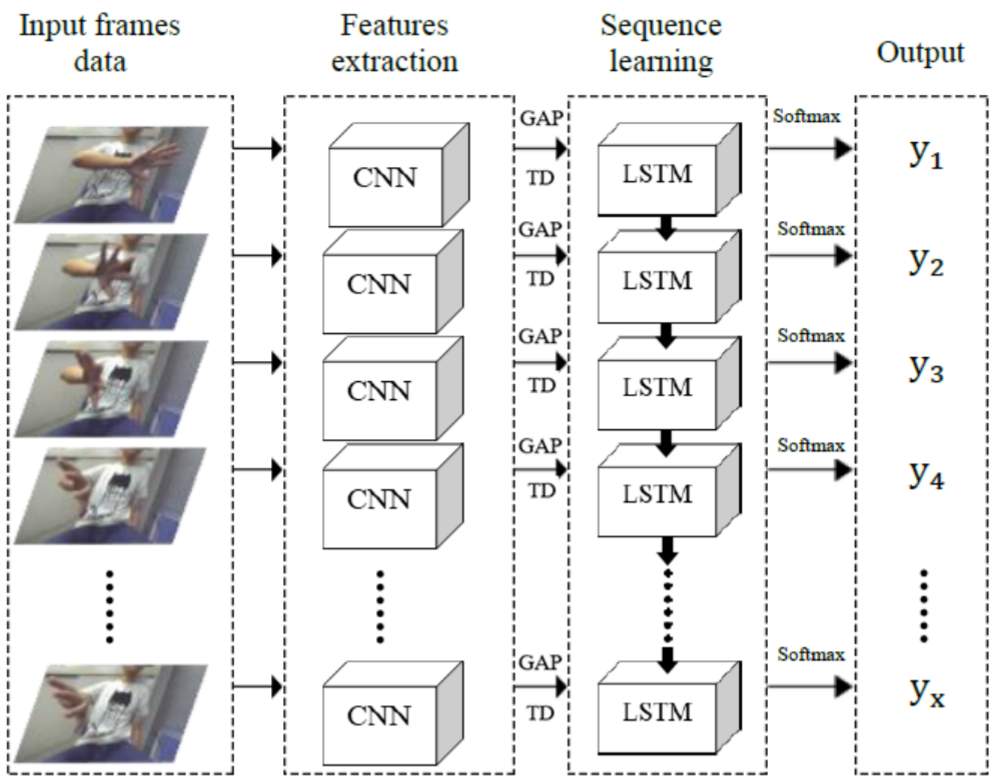

Figure 5.1 – Scheme of data processing through CNN-LSTM model.

This chapter builds upon the foundations laid in the preceding Chapter 4, where the state-of-the-art approaches in the field were elucidated. This chapter sections delves into the details of the proposed model, its architecture, and the methodologies employed, aiming to contribute novel insights and advancements to the realm of human activity recognition.

5.1 Datasets

Research in HAR relies on various datasets that serve as benchmarks for evaluating the performance of different algorithms and techniques. Prominent among these datasets are UCF101, HMDB51, Kinetics, ActivityNet, and NTU RGB+D, as highlighted in (PAREEK; THAKKAR, 2021). These datasets encompass diverse video clips, featuring action categories spanning from simple to highly complex.

The UCF101 dataset stands out as a widely embraced benchmark for action recognition. Originally curated by the Center for Computer Vision Research at the University of Central Florida in 2012, the dataset comprises 13,320 videos showcasing various human actions. These videos, initially acquired from YouTube, cover a spectrum of 101 action categories. The UCF50 dataset, which had 50 activity categories, has evolved into the UCF101 dataset. For every action category, UCF101's activities are arranged into 25 groups, providing a thorough portrayal of a variety of human motions.

It's important to note that Python libraries like OpenCV and Numpy are used to split the video into frames in order to generate UCF101. Owing to computational limitations, however, this study makes use of the UCF50 dataset, which preserves the essential features of UCF101 but has a more manageable set of 50 action categories. This deliberate choice preserves compatibility with computing resources while utilizing a large dataset to investigate various approaches for Human Activity Recognition.

5.2 Data Video Processing

The data video processing outlined in this section is illustrated in Figure 5.2 and can be succinctly summarized as follows:

1. **Pre-processing the Dataset:** Initially, the video undergoes segmentation into frames with a sequence length of 20. Notably, not all frames are included; rather, a select set of dispersed frames with a sequence length of 20 are sanctioned for further processing. To prevent any potential bias, the dataset is shuffled prior to this segmentation, ensuring that the splits are representative of the overall data distribution. An illustrative depiction of the input data is presented in Figure 5.3.

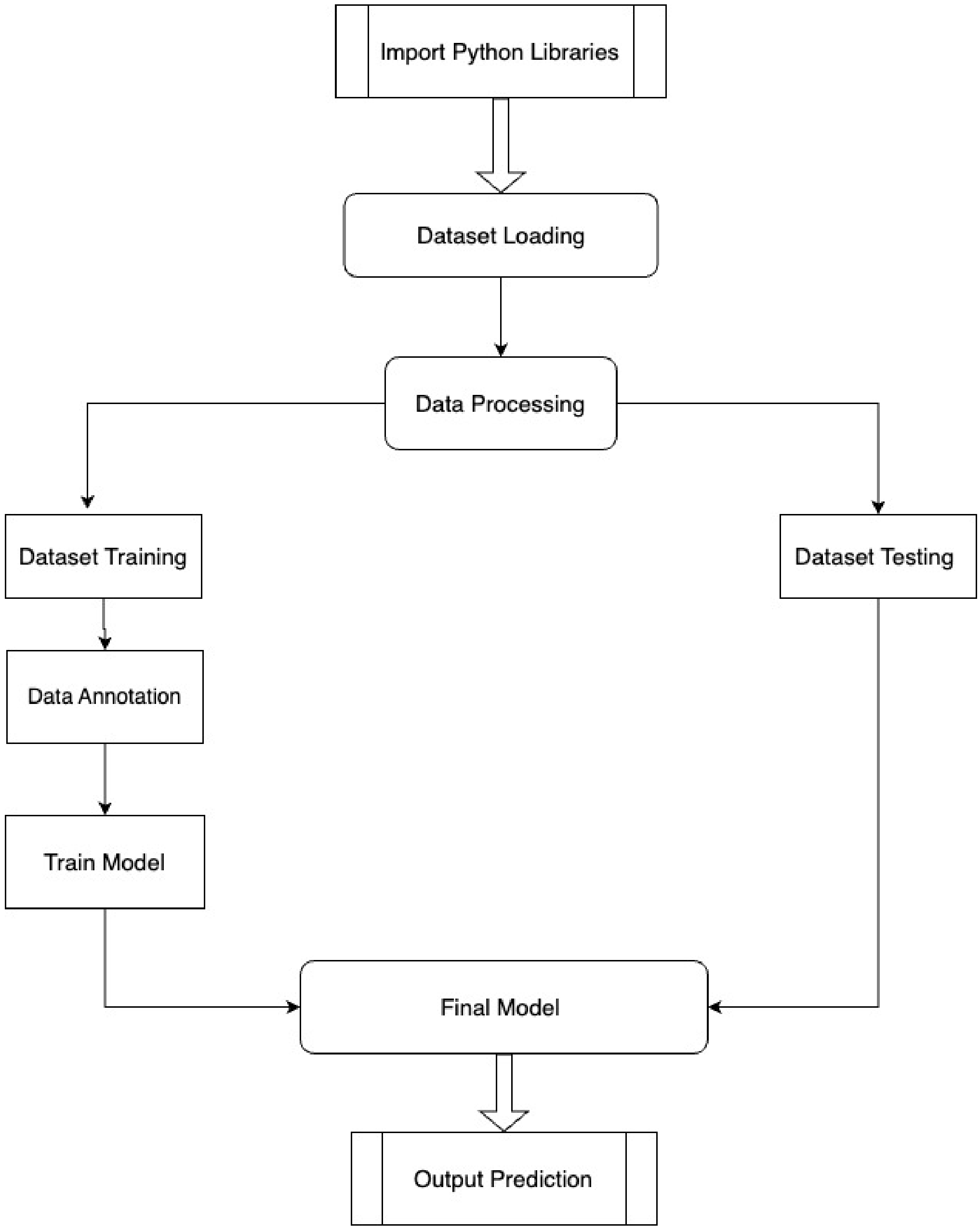

Figure 5.2 – Data Processing System Architecture

2. **Dataset Splitting and Training:** Typically, 25% of the dataset is put aside for testing and 75% of the dataset is used for training. The CNN-LSTM model receives the data from both sets after it has been converted into hot encoding vectors (refer to Figure 5.1). Subsequently, the model undergoes evaluation, leading to the generation of value and loss graphs.

3. **Model Training and Testing Procedure:** Within this phase, the model systematically selects three random classes during each iteration of the training and testing processes. The films' frames are simultaneously scaled while keeping the same width and height. This resizing serves to standardize the data range to [0-1] and also makes it possible to reduce the computational load during training. Normalization, which

is accomplished by dividing the frame values by 255, accelerates the convergence of the data and improves the effectiveness of the network training procedure.

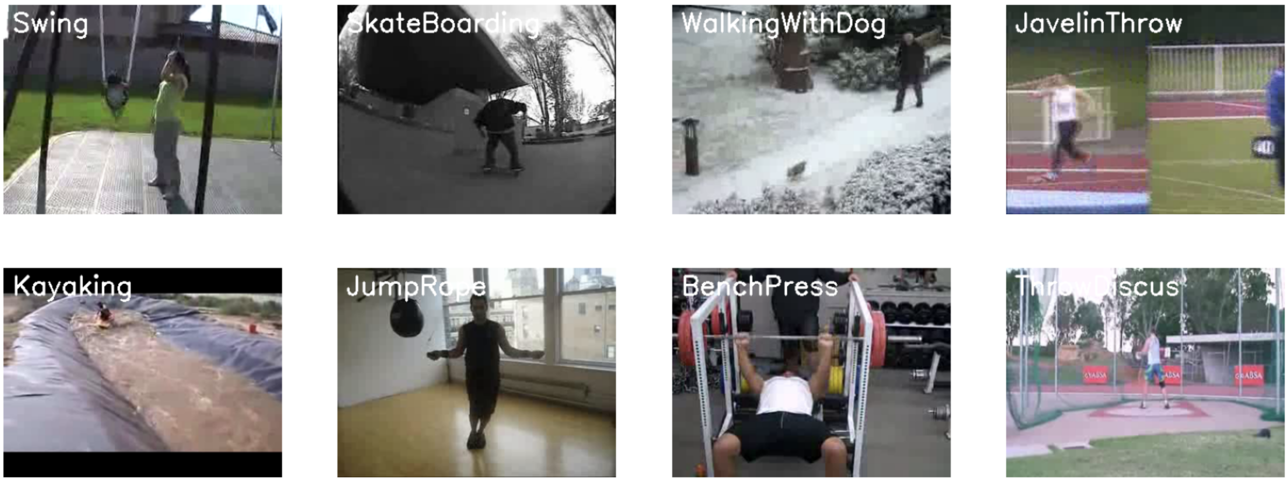

Figure 5.3 – Example of input frame data.

5.3 Simulation and Results

The simulation was conducted within a Jupyter Notebook environment using Google Colaboratory and implemented in Python 3. It's worth noting that the libraries utilized are resource-intensive and demand significant computational power, hence it is advisable to execute the simulation on Google Colab. Additionally, the dataset employed, UCF50, is substantial in size, comprising 50 classes, each containing over 50 videos. Access to the UCF50 dataset is available for download from here.

A CNN-LSTM model was simulated for a classification task. The model is compiled using the categorical cross-entropy loss function and the Adam optimizer. Training is performed on the provided training data with a batch size of 4 and for 10 epochs. This epoch limit is chosen to mitigate the risk of code crashing, which tends to increase beyond 12 epochs. Validation data is set to 20% of the training data, and early stopping is applied with a patience of 10 epochs to counter overfitting. The training history of the model is stored in the variable named CNN-LSTM model training history.

The variables features train, features test, labels train, and labels test now hold the split data. These can be employed to both train and test the CNN-LSTM machine learning model effectively.

The confusion matrix depicted in Figure 5.4 provides an assessment of the classification model's performance across the following classes:

- Walking with dog,
- Taichi,
- Swing,
- Horse race.

This matrix illustrates the frequency of predictions made for each class in comparison to the actual labels present in the dataset. Each row corresponds to the true labels of the data, while each column indicates the predicted labels generated by the model.

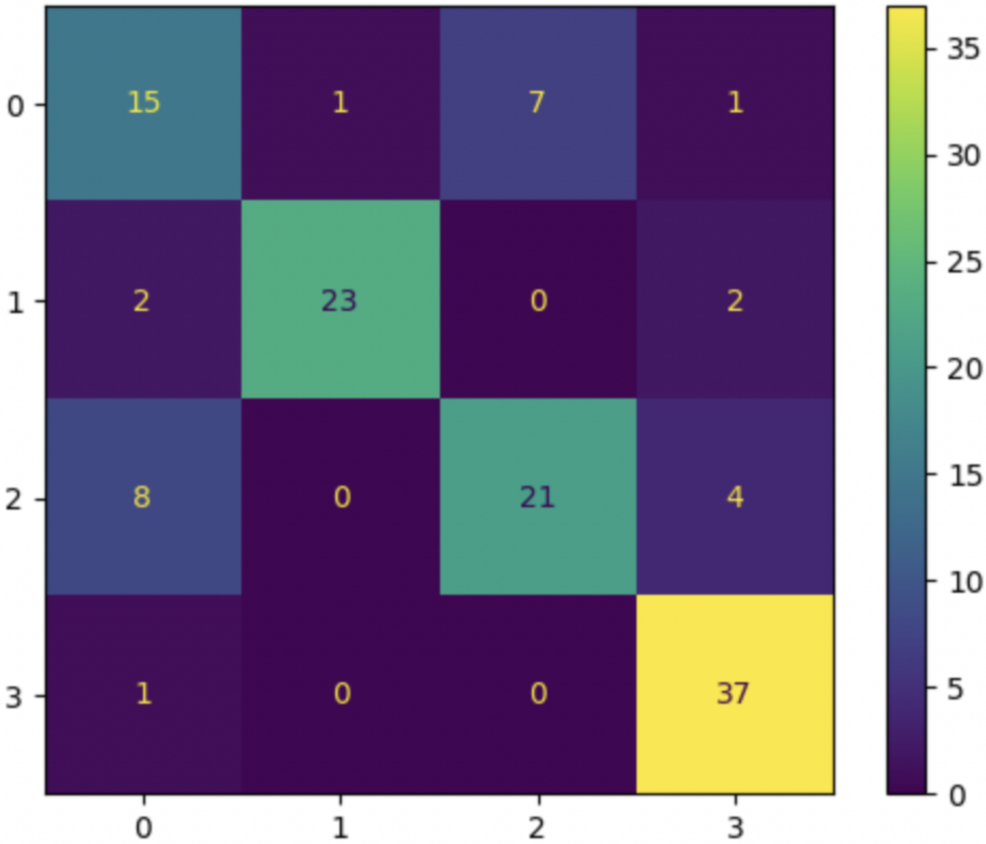

Figure 5.4 – CNN-LSTM model confusion matrix. 0 represents Walking with dog, 1 represents Taichi, 2 represents Swing, and 3 represents Horse race.

The diagonal elements, running from the top left to the bottom right of the matrix, signify the count of correctly classified samples for each class. Specifically, in this scenario, 15 samples are accurately predicted as Walking with a dog, 23 samples as Taichi, 21 samples as Swing, and 37 samples as Horse race.

The training accuracy was visualized alongside the validation accuracy across iterations to evaluate the performance of two approaches: ConvLSTM and LRCN. These visualizations are presented in Figure 5.5 and Figure 5.6, respectively.

For the CNN model, training accuracy reached up to 80%, while validation accuracy concurrently peaked at 90%, as illustrated in Figure 5.5.

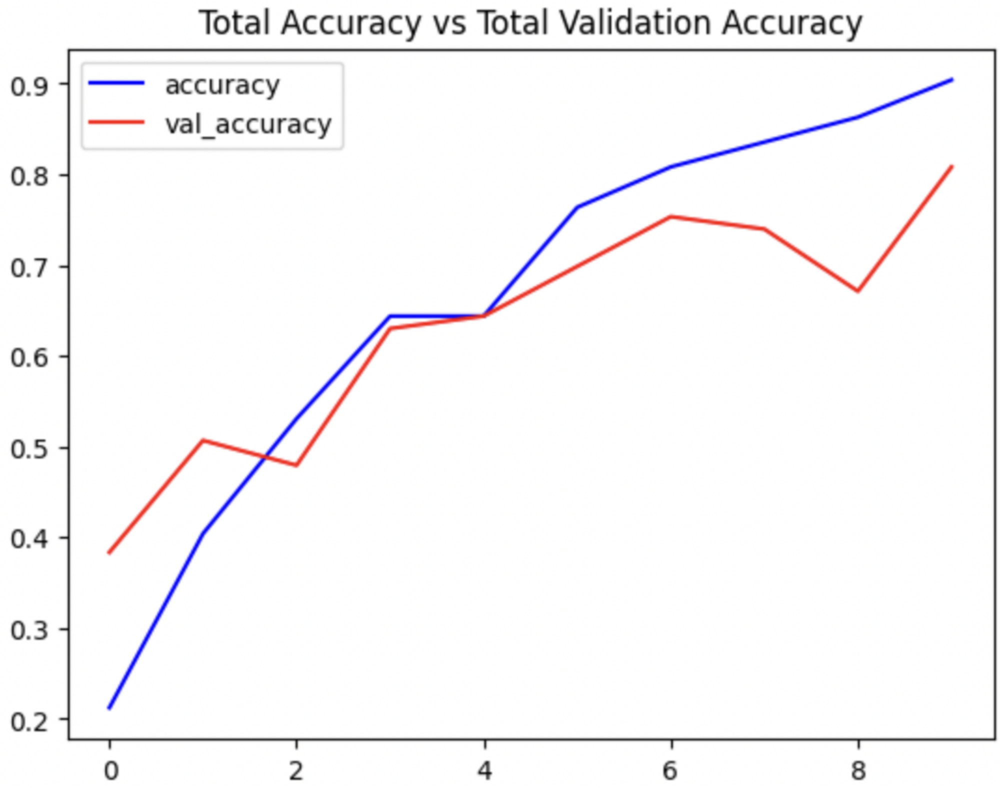

Figure 5.5 – ConvLSTM model training History Accuracy

The comparatively lower validation loss observed in both approaches ensures that the model did not overfit. This is depicted in Figure 5.7 and Figure 5.8, showing the training and validation loss for the ConvLSTM and LRCN approaches, respectively.

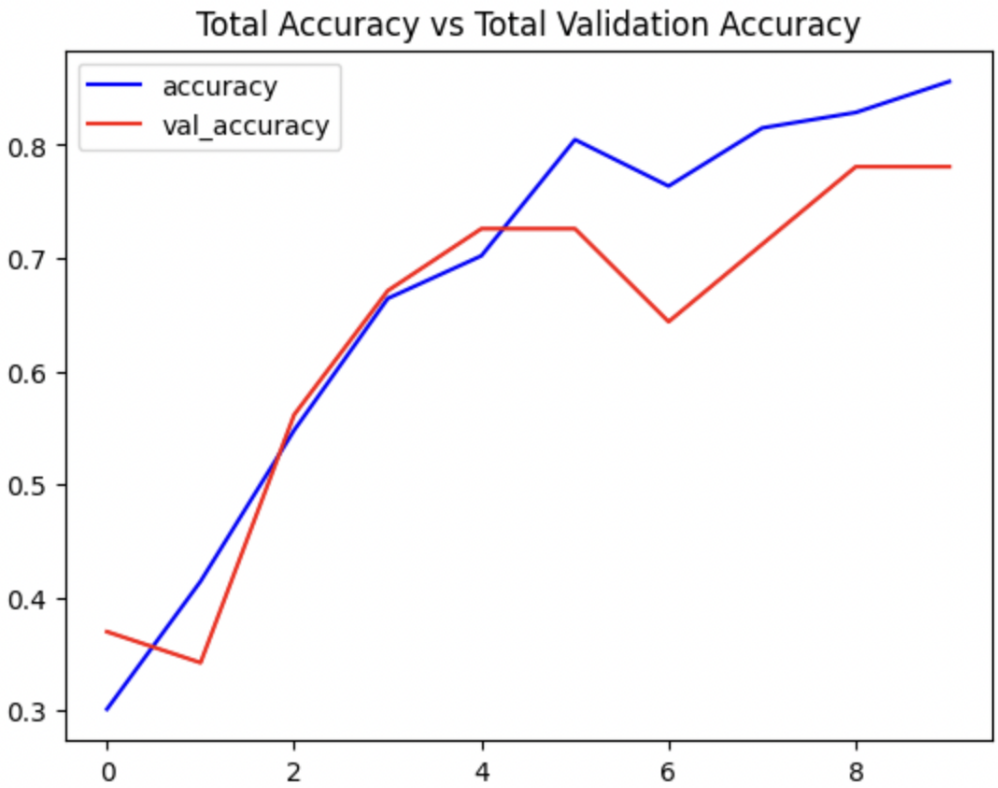

Figure 5.6 – LRCN model training History Accuracy

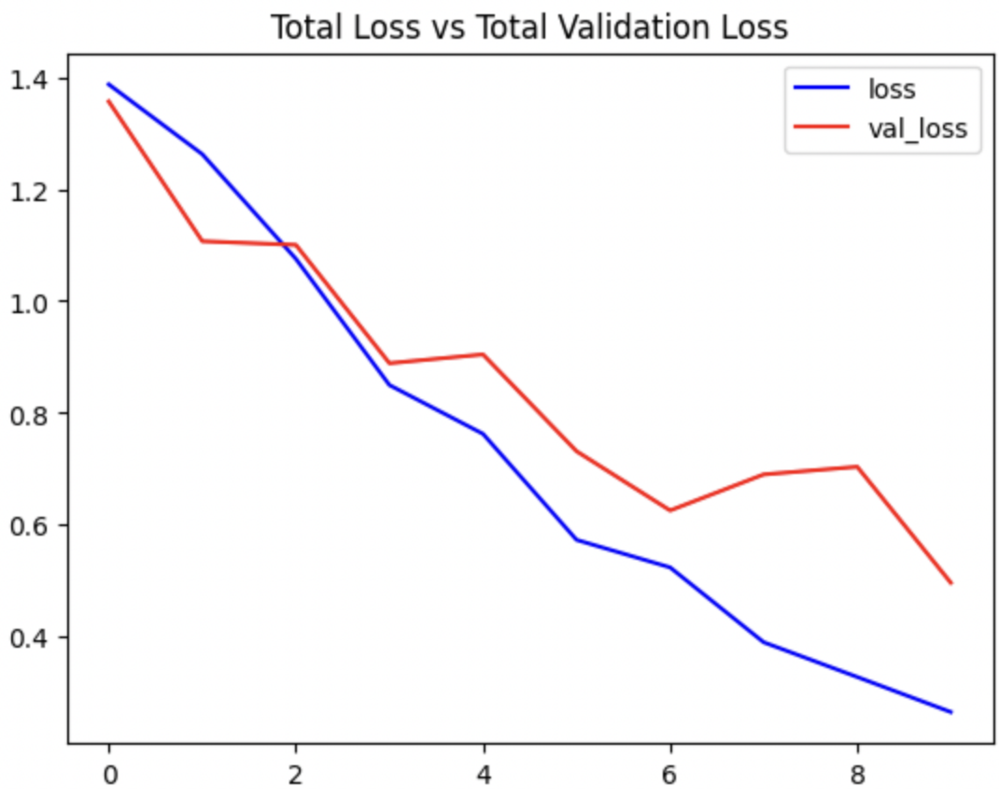

Figure 5.7 – ConvLSTM model training History Loss

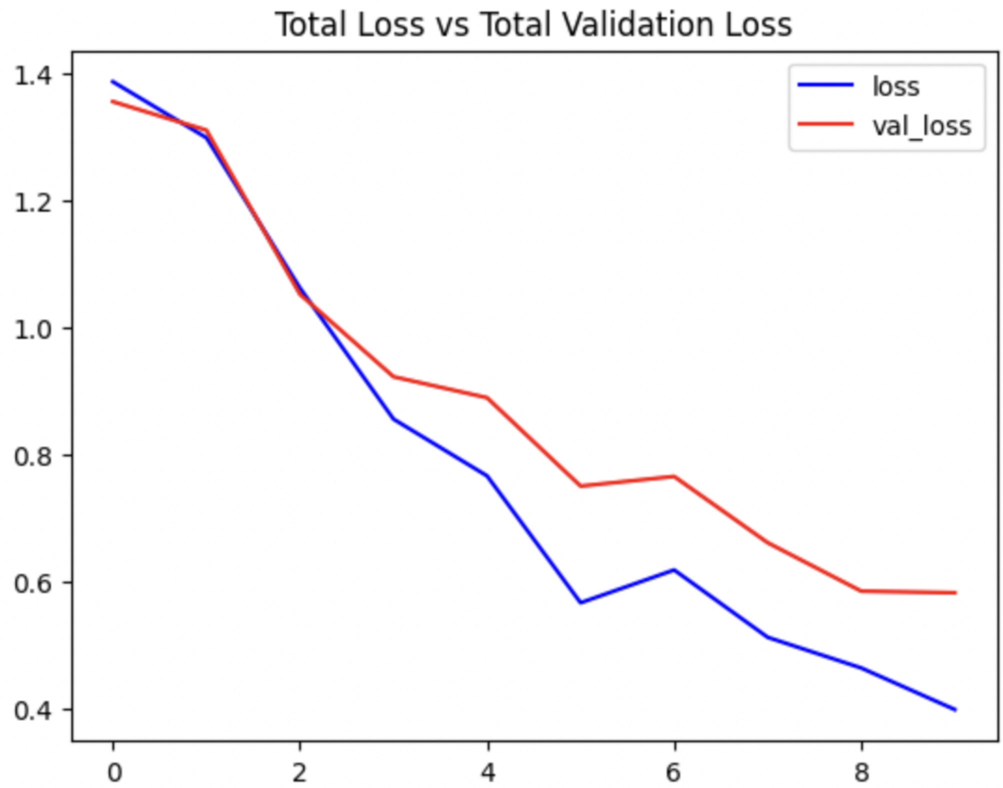

Figure 5.8 – LRCN model training History Loss

During the simulation process, the layer configurations for ConvLSTM and LRCN are outlined in Table 5.1 and 5.2 respectively. Each table consists of three columns: Layer (type), Output Shape, and Param #. These columns detail the type of layer, the output shape, and the number of parameters (#) associated with each layer in the neural network. The values are populated based on the provided data.

Furthermore, at the bottom of each table, the total counts of trainable and non-trainable parameters are presented. Vertical lines divide each column, facilitating the distinct separation of information, while horizontal lines are used at the top and bottom of the tables to improve readability and organization. Understanding the design and parameterization of the ConvLSTM and LRCN models used in the simulation is made easier with the help of these tables.

A neural network model's layer configuration and parameter details are shown in the Table 5.1. Multiple ConvLSTM2D layers, recurrent neural network layers intended to carry out convolutional operations on input patterns, make up the model's architecture. The time-distributed and max pooling layers come after these layers in order. The time-distributed layers guarantee that the same function is applied to each time step in the sequence, which helps with sequence processing, while the max pooling layers serve to decrease the output's dimensions.

The last layers of the network consist of a flattened layer that makes the

Table 5.1 – Layer Configuration of the ConvLSTM

Layer (type)	**Output Shape**	**Param #**
conv_lstm2d	(None, 20, 62, 62, 4)	1024
max_pooling3d	(None, 20, 31, 31, 4)	0
time_distributed	(None, 20, 31, 31, 4)	0
conv_lstm2d_1	(None, 20, 29, 29, 8)	3488
max_pooling3d_1	(None, 20, 15, 15, 8)	0
time_distributed_1	(None, 20, 15, 15, 8)	0
conv_lstm2d_2	(None, 20, 13, 13, 14)	11144
max_pooling3d_2	(None, 20, 7, 7, 14)	0
time_distributed_2	(None, 20, 7, 7, 14)	0
conv_lstm2d_3	(None, 20, 5, 5, 16)	17344
max_pooling3d_3	(None, 20, 3, 3, 16)	0
flatten	(None, 2880)	0
dense	(None, 4)	11524
Total params		44,524
Trainable params		44,524
Non-trainable params		0

Table 5.2 – Layer Configuration of the LRCN

Layer (type)	**Output Shape**	**Param #**
TimeDistributed	(None, 20, 64, 64, 16)	448
TimeDistributed	(None, 20, 16, 16, 16)	0
TimeDistributed	(None, 20, 16, 16, 16)	0
TimeDistributed	(None, 20, 16, 16, 32)	4640
TimeDistributed	(None, 20, 4, 4, 32)	0
TimeDistributed	(None, 20, 4, 4, 32)	0
TimeDistributed	(None, 20, 4, 4, 64)	18496
TimeDistributed	(None, 20, 2, 2, 64)	0
TimeDistributed	(None, 20, 2, 2, 64)	0
TimeDistributed	(None, 20, 2, 2, 64)	36928
TimeDistributed	(None, 20, 1, 1, 64)	0
TimeDistributed	(None, 20, 64)	0
LSTM	(None, 32)	12416
Dense	(None, 4)	132
Total params		**73,060**
Trainable params		**73,060**
Non-trainable params		**0**

output into a one-dimensional array and a dense layer that makes the input data linear transformations. There are 44,524 trainable parameters in the overall model, all of which are used in the training phase. The table lists the parameter counts for each layer and gives brief explanations of the layer structure. Understanding this information is essential to properly modifying the model's hyperparameters and understanding its design.

The classification model's performance metrics are shown in Table 5.3 for four different classes, denoted as 0, 1, 2, and 3. The precision, recall, and F1-score for each class are displayed in the table, giving detailed information on how well the model classified each category.

Table 5.3 – CNN-LSTM Classification Report

Class	**Precision**	**Recall**	**F1-Score**	**Support**
0	0.58	0.62	0.60	24
1	0.96	0.85	0.90	27
2	0.75	0.64	0.69	33
3	0.84	0.97	0.90	38
Accuracy			0.79	122
Macro Avg	0.78	0.77	0.77	122
Weighted Avg.	0.79	0.79	0.78	122

The percentage of anticipated cases that are accurately identified for a given class is known as precision. Conversely, recall indicates the proportion of true instances of a class that are correctly classified. The F1-score is a balanced statistic that provides a thorough assessment of the model's performance by taking both accuracy and recall into account at the same time. It is computed as the harmonic mean of precision and recall.

Within the class 0 context, the precision of 58% means that only 58% of all instances expected to be class 0 are in fact class 0. With a recall of 62%, 62% of real occurrences in class 0 are said to be accurately classified. The F1-score, which is 60%, is a fair evaluation because it accounts for both recall and precision in its computation.

Class 1 cases are predicted by the model with great accuracy, as evidenced by its precision of 96%. A recall of 85% indicates that 85% of all real cases of class 1 are successfully identified by the model. Moreover, the F1-score, which is calculated using both precision and recall, indicates a well-balanced performance at 90%.

When it comes to class 2, a precision of 75% means that 75% of all anticipated occurrences are correctly identified by the model as being in class 2. With a recall of 64%, the model is able to accurately identify 64% of all real instances of class 2. Furthermore, the F1-score, which is 69%, exhibits a balanced assessment as it computes both precision and recall.

A precision of 84% in the context of class 3 means that 84% of all predicted occurrences allocated to class 3 are correctly identified by the model. The model successfully recognizes 97% of all real occurrences that belong to class 3 with a recall of 97%. In addition, the F1-score, which is 90%, shows a fair evaluation because it takes memory and precision into account.

The accuracy of the CNN-LSTM model is 79%, which is the proportion of all cases that are properly classified. The average of these metrics over all four classes, with equal weights given to each class, yields the macro-average of precision, recall, and F1-score, which is 78%. Furthermore, the precision, recall, and F1-score weighted average is 79%. This is achieved by averaging these metrics over all four classes, taking into account the number of instances in each class for weighting.

Three CNN-based methods that use CNNs for feature extraction are shown in the Table 5.4. Context Stream, VGG-M-2048, and CNN Based ResNet 50. They vary, meanwhile, in the CNN architecture that is used. Context Stream method (KARPATHY *et al.*, 2014) uses distinct streams to analyze temporal and spatial data, while deep CNNs like ResNet-50 and VGG-M-2048 are meant to learn high-level features. On the UCF dataset, ResNet-50 performs the best among these three algorithms, with an accuracy of 94.2%, followed by VGG-M-2048 (92.5%) and Context Stream (63.3%).

Furthermore, several models are used by RNN Based ConvNet+LSTM and hybrid-based SVM for feature extraction and classification. While RNN Based ConvNet+LSTM uses both CNNs and LSTMs for feature extraction, hybrid-based SVM combines SVM with manually created features. The Skeleton Based 2S-EGCN approach, on the other hand, is notable for using graph convolutional networks (GCNs) on skeleton data to extract features. On the NTU-RGB+D dataset, a benchmark for 3D action recognition, this method achieves state-of-the-art performance.

The methods RNN Based GoogleLeNet (88.5%), RNN Based LSTM (89.11%), and Combined Based C3D+SVM (89%) all leverage Recurrent Neural Networks (RNNs) for feature extraction, yet they vary in the specific type of RNN utilized and how it integrates with other models. RNN Based GoogleLeNet adopts a modified version of the GoogleLeNet architecture, incorporating an LSTM layer. Conversely, RNN Based LSTM exclusively employs LSTM networks for feature extraction.

When considering computational complexities, approaches such as CNN Based VGG-M-2048, CNN Based ResNet 50, RNN Based GoogleLeNet, and Combined Based C3D+SVM are all resource-intensive and typically necessitate implementation in well-equipped laboratories. However, it's noteworthy that despite achieving an accuracy of 79%, the CNN-LSTM method demonstrates competitive performance within the same computational environment, as illustrated in Table 5.4.

Table 5.4 – Efficiency of CNN-LSTM as compared to other methods.

Approach	**Model**	**Dataset**	**Accuracy(%)**	Publish year
CNN Based	Context-Stream (KARPATHY *et al.*, 2014)	UFC	63.3%	2014
CNN Based	VGG-M-2048 (FEICHTENHOFER *et al.*, 2016)	UFC	92.5%	2016
CNN Based	ResNet 50 (ZHENG; ZHANG, 2021)	UCF	94.2%	2016
Hybrid Based	SVM (SHUVO *et al.*, 2020)	UCI-HAR	91.15%	2017
RNN Based	ConvNet+LSTM (NAEEM *et al.*, 2021)	UCF	89.2%	2018
Skeleton Based	2S-EGCN (WANG *et al.*, 2022)	NTU-RGB+D	95.5%	2022
RNN Based	GoogleLeNet (YU *et al.*, 2019)	UCF	88.5%	2020
RNN Based	LSTM (DAI *et al.*, 2020)	UCF	89.11%	2020
Combined Based	C3D+SVM (LI *et al.*, 2018)	UCF	89.0%	2021
Our Method	**CNN+LSTM**	**UCF**	**79%**	**2023**

6 Conclusions and Future Works

This chapter presents the concluding remarks of the thesis and future research works.

6.1 Conclusions

This conclusion chapter underscores the integration of advanced technologies like IoT, 5G, and machine learning, which holds immense potential to revolutionize urban development, sentiment analysis, and human activity recognition. By continuing to explore and refine these technologies, we can create smarter, more efficient systems that significantly enhance the quality of life and provide valuable insights across various domains.

- **Chapter 2**

There is an increasing global trend towards making cities smarter, with a common strategy centered on urban development through Information and Communication Technologies (ICT). Despite varied definitions of smart cities, they all emphasize leveraging ICT to gather and process crucial data to enhance infrastructure, services, and ultimately, the quality of life for citizens.

At the heart of smart city services is the Internet of Things (IoT), which facilitates the integration of various urban sectors through sensors, communication protocols, and data management and analysis systems. However, effective IoT implementation hinges on robust telecommunication infrastructure, as it involves a large number of devices transmitting data simultaneously in a concentrated area. This necessitates infrastructure that can support high connection density and low latency.

This is where the importance of 5G technology arises. The demanding needs of the Internet of Things in smart cities are addressed by the architecture of the fifth generation of mobile networks. 5G networks are anticipated to have upgraded requirements beyond existing 4G capabilities, including the ability to support at least 1,000,000 devices per square kilometer with a maximum latency of 10 milliseconds.

Governments and city administrators worldwide recognize the importance of updating their telecommunications infrastructure to accommodate 5G and its associated services. However, the process is complex and time-consuming, with each country adopting strategies that align with their unique circumstances. The COVID-19 pandemic has also caused significant delays and disruptions.

The deployment of 5G is varied between nations. For example, the fiber optic backbones of Guyana and Paraguay are currently being established. During the transition time, limited 5G services are being provided by Ecuador, Peru, Brazil, Argentina, and Ecuador using their current 4G infrastructure. Having found reputable businesses, Chile and Venezuela are currently installing. Several towns in Bolivia, Colombia, and French Guiana have activated 5G, and the networks are presently undergoing testing. Commercial 5G is available in Suriname and Uruguay, but it's restricted to certain regions.

Despite these varying stages of development, all countries are progressing towards the global trend of integrating 5G, IoT, and smart city technologies. The goal is to create smarter, more efficient cities that improve the quality of life for their citizens through advanced technological infrastructure.

- **Chapter 3**

This chapter delineates the comprehensive process of data collection, text pre-processing, and sentiment analysis conducted on Twitter data, focusing on the 2021 Ecuadorian presidential election. Utilizing libraries such as Sentiment Spanish, TextBlob, and Vader, we performed an extensive sentiment analysis of tweets related to the two main candidates, Arauz and Lasso.

Our findings reveal a significant divergence in sentiment classification between the tools used. The Sentiment Spanish library predominantly classified the tweets as negative for both candidates. Conversely, TextBlob and Vader, which demonstrated superior performance in sentiment analysis, identified most tweets as positive, followed by neutral polarity.

The study involved several steps, such as sentiment analysis based on polarity, stemming, text extraction, and preprocessing. A thorough analysis of the tweet data was also carried out, revealing the terms that each candidate used most and least frequently as well as highlighting their frequency of usage. This investigation shed light on the many sentiment and emotional patterns that were evident in the candidates' discussions.

Frequency and distribution graphs, among other visual displays of the data, made it easier to comprehend the attitudes and feelings expressed in the tweets. These graphics not only made the findings easier to understand, but they also demonstrated how effective the techniques used in this study were.

In conclusion, by illustrating the suitability and precision of diverse sentiment analysis techniques in the interpretation of social media data, this chapter makes significant contributions to the field of sentiment analysis in political situations. The knowledge gained from this study can guide future sentiment analysis research and approaches, especially in political and electoral contexts.

- **Chapter 4 and Chapter 5**

These chapters have examined several methods for recognizing human activity, with a focus on the effectiveness of Long Short-Term Memory (LSTM) and Convolutional Neural Networks (CNNs). The extraction of features from photos or videos has been successfully accomplished by CNNs; however, the temporal dynamics of human movements are best captured by Skeleton-Based, Sensor-Based, and LSTM models. Investigations have also been conducted into alternative strategies like Support Vector Machines and Decision Trees. The particular application requirements, such as the type of data, the quantity of actions to be identified, and the available computational resources, will ultimately determine which approach is best.

Using CNN and LSTM, this study has carried out a thorough examination of human activity recognition in video frames using two different methodologies: ConvLSTM and Long-term Recurrent Convolutional Networks (LRCN). Based on the spatiotemporal information in video frames, the suggested CNN-LSTM technique can efficiently and accurately identify human actions, according to the findings. Key parameters such as the activation function, optimizer type, learning rate, number of training epochs, dropout rate, batch size, and the number of neurons in the CNN-LSTM model significantly impact accuracy. Optimal settings are crucial for achieving high performance.

The CNN-LSTM model demonstrated superior robustness and reliability in recognizing human activities compared to statistical machine learning approaches. Performance evaluation showed that the CNN-LSTM model achieved 79% accuracy with 10 training epochs on the UCF dataset. This suggests the proposed method can outperform other methods requiring 25 to 30 epochs. The primary constraint limiting the CNN-LSTM method to 10 epochs was computational limitations. Extending training to 25 epochs resulted in a 94% accuracy but encountered instability around 18 epochs. Thus, 10 epochs were deemed the most stable for balancing computational complexity and prediction performance.

Additionally, the model achieved an 84% precision rate based on correctly classified activities and a 97% recall rate. The ConvLSTM model successfully captured both spatial and temporal dependencies in video sequences, offering a comprehensive understanding of human activity. The collaboration between CNN and LSTM allowed the model to learn high-level spatial features and temporal motion, resulting in an improved F1 score of 90%.

The integration of 5G with sentiment analysis and human activity recognition using CNN-LSTM enables the development of advanced smart solutions. 5G provides the necessary infrastructure to support rapid data analysis and processing in real time. In this context, sentiment analysis delivers timely predictions to evaluate public opinion on political issues, while CNN-LSTM networks optimize and validate human activity recognition. Together, these technologies propel urban development and innovation

6.2 Future Works

In this section, some proposals related to the contributions and results of this thesis can be studied in the future, such as:

- **Exploration of 6G Implementation in South America:** Future research could investigate the potential deployment and implications of 6G technology in South America. This study would include technological advancements, infrastructure requirements, and socio-economic impacts. A comparative analysis with 5G could provide insights into the benefits and challenges of transitioning to 6G.

- **Enhanced Sentiment Analysis Techniques for Political Campaigns:** Building upon the sentiment analysis of Ecuadorian presidential elections, future work could focus on refining sentiment analysis techniques using more advanced natural language processing (NLP) models. This research could explore the use of transformers, such as BERT or GPT, to achieve more accurate and nuanced sentiment detection in political discourse across different South American countries.

- **Real-time Sentiment Analysis for Electoral Predictions:** Another promising direction is the development of a real-time sentiment analysis system for predicting electoral outcomes. By continuously monitoring social media platforms and news outlets, this system could provide early indicators of public opinion shifts and election trends, offering valuable insights for political analysts and campaign strategists.

- **Integrating IoT and 5G for Smart City Applications in South America:** This proposal aims to investigate the integration of Internet of Things (IoT) devices with 5G networks to develop smart city applications. The research could focus on case studies in various South American cities, assessing the effectiveness and efficiency of 5G-enabled IoT solutions in areas such as traffic management, energy consumption, and public safety.

- **Improving Human Activity Recognition with Hybrid Deep Learning Models:** Future research could enhance CNN-LSTM-based approaches for human activity recognition by incorporating hybrid deep learning models. Combining convolutional neural networks (CNNs) with other recurrent neural network (RNN) architectures, such as GRUs or attention mechanisms, could improve the accuracy and robustness of activity recognition systems, with applications in healthcare, sports, and security.

- **Cross-Cultural Sentiment Analysis in Latin American Elections:** Expanding on the sentiment analysis of Ecuadorian elections, a comparative study of sentiment across multiple Latin American countries during election periods could provide deeper insights into regional political dynamics. This research could analyze the differences and similarities in voter sentiment, campaign strategies, and media influence, contributing to a broader understanding of political behavior in the region.

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