Addis Ababa institute of Technology

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Deep Learning Based User Mobility Prediction

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Declaration

I, the undersigned, declare that this thesis is my original work, has not been presented for a degree in this university, and all sources of materials used for the thesis have been fully acknowledged.

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Place: Addis Ababa

Date of Submission:______________________________

This thesis has been submitted for examination with my approval as a university advisor.

Dr. Tsegamlak Terefe ______________________________

Advisor's name Signature

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Abstract

Telecommunication service providers mainly emphasize on providing uninterrupted network access with the maximum attainable quality of service. With this in mind, service providers often monitor and utilize information acquired from user mobility patterns to performing effective resource management of network resources and to predict the user's future location. For instance, information associated with user mobility is used to reduces the cost of paging, managing the bandwidth resources and efficient planning. Overall, with the current trend of increase in the number of devices connected to mobile networks, telecom service providers are expected to carefully monitor and utilize user mobility patterns in order to improve the quality of service provided to their customers.

With this understanding, in this thesis, we propose to utilize neural networks to predict user mobility, which helps to increase the performance of mobility analysis in cellular networks. This in turn is expected to improve the studying and under. In general, we intend to provide useful insights into how users migrate across various geographic areas and how they interact with the network infrastructure supplied by Ethiotelcom by constructing neural network based user predicting models. To meet this objective, we used mobility data obtained from Call Details Records (CDR) to forecast the future mobility of users (devices) as a sequential time series. Our experimental outcome suggests that a neural network based on one dimensional convolutional effective tool for user mobility analysis using datasets extracted from CDR. In reality, the Conv-LSTM networks take advantage of both an LSTM's ability to capture long-short dependency for time series data and the strength of the convolutional layers to extract localized features from complicated and non-linear dataset.

Keywords*– Telecom carriers, Mobility prediction, Resource Management, Deep Learning,cellular network.*

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List of Abbreviation

3GPP	3rd Generation Partnership Project
5G	Fifth Generation
CDR	Call Details Records
eNBs	Evolved Node Bs
GPS	Global Positioning System
HMM	Hidden Markov Models
IMSI	International Mobile Subscriber Identity
IoTs	Internet of Things
LTE	Long Term Evolution
M2M	Machine-to-Machine
MME	Mobility Management Entity
MMM	Mixed Markov chain Model
MNOs	Mobile Network Operators
STF-RNN	Time-series Forecasting- Recurrent Neural Networks
TAU	Tracking Area Update
UE	User Equipment

Chapter 1

Motivation and Background

1.1 Introduction

One of the crucial invention over the past decades is the emergence of mobile networks with the ability to make intelligent judgments to the demands of various service requests. This innovation has helped mobile network operators to provide a wide range of automated applications for prospective mobile end users in the area of internet of things. For instance, mobile users are able to conduct business, complete transactions, and enhance their mobile phone usage while they are in motion. Moreover, users may also conduct impromptu teleconferences, surf the internet, see high definition movies, listen to audio on the run, communicate to distant relatives, post images or videos to social media, etc. [1, 2, 3].

Practically, in addition to establishing user regulations, mobile network operators are expected to work hard to accommodate ever increasing demands by providing the resources necessary to ensure that mobile services are available to all interested users. In other words, the innovation that enhances the quality of life for every mobile user must address the increasing traffic needs which is expected to increase significantly within the next few years [4, 5, 6, 7]. In reality, the increase in the demand of resources is highly correlated to advancements made in the application domain. The wireless communication industry is now experiencing rapid growth in mobile communication. Mobility prediction is one of the key enablers that uses historical traffic information to predict future locations of traffic users. Accurate mobility prediction can help enable effective radio resource management, assist route planning, guide vehicle dispatching, or mitigate traffic congestion. Mobility prediction has been widely applied to mobile communication due to the increasing capacity requirements and requirements for quality of experience.

Overall, due to the mentioned and unmentioned reasons, data traffic generated by communication devices which is often linked to networks through Call Details Records (CDRs) has significantly increased. Consequently, telecom operators, such as Ethio-telecom, have now access to a vast quantity of data which could be utilized to raise the quality of service provided to their customers [8, 9]. In this regard, researches show that data flow from cellular networks,i.e., 2G/3G/4G/5G, is very helpful for studying human dynamics and providing trajectories of individuals on a big scale. For instance, by tracking people's movements' it is possible to gain the advantages of minimal energy usage, extensive coverage of a big population, and great cost effectiveness [10]. Moreover, mobility prediction is used in wireless networks to manage bandwidth resources and facilitate effective planning[11]. Overall, wireless networks use mobility prediction to execute efficient network resource management by forecasting a user's future position [12].

Even though predicting user mobility proved to be useful, selecting a proper predictive model is crucial in guaranteeing the usability (interpretability) of predicted outcomes. In this regard, deep learning-based (also called Deep Trip) algorithms have proved to be useful in forecasting a person's travel schedule in the future, even to possible departure times. For instance, [13] have shown that neural networks able to predict travel-related data, including destinations, departure times, and maybe additional specifics like mode of transportation, length of trip, and more. In reality, the forecasts aware made by observing previous travel data and sometimes additional relevant parameters. Generally, deep neural networks are a useful tool for machine learning and artificial intelligence in the field of wireless communication and network management because they may be used to predict the future locations of wireless network users. Overall, the use of deep neural networks to forecast the future locations of wireless network users is a potent tool for increasing services, managing the network better, and providing consumers with a seamless and effective wireless communication experience.With this idea, we will present the statement of the problem we propose to address in this thesis.

1.2 Problem Statement

Ethio-telecom, one of the telecom service provider in Ethiopia, is continuously working to raise the quality of service for its customers. However, maintaining quality of service is not a trivial task due to the rise in the number of devices connected to its mobile networks.

Despite this fact, the ethiotelecom company is aims to make sure that customers (devices connected to its mobile networks) have constant access to a faster network with uninterrupted access with a lower cost at the operator side . In this regard, some of the measures taken by the company includes, to turn off base stations or scale back their capacity during times of low traffic, conserving energy and lowering operational costs. Practically, a base station (radio unit) is expected to swiftly ramp up its capacity to meet an increasing demand, i.e., User Equipment (UE) are anticipated to enter a region. For instance, radio units are expected to allocate communication channels in the case of handover. In practice, better spectrum usage can result from efficient resource allocation based on mobility forecasts.

Practically, network operators such as Ethio-telecom, can improve the quality of service they provide by considering user's mobility. In the context of network operators, mobility prediction algorithms lets telecom companies to foresee how users' equipment (UEs) will move between base stations or cells. This in turn help operators to dynamically modify bandwidth and additional resources allocated to base station. For instance, the operator can provide enough base station additional bandwidth if it is expects an influx of UEs would move into a certain location. Thus, ensuring continuous service and better network speeds. Moreover, by taking such measures, resources can be distributed more effectively to areas with fewer projected UEs reducing operational expenses. Consequently, mobility prediction can help in load balancing between base stations. In this regard, network operators can divide the load across nearby base stations to avoid network congestion by anticipating UE movement patterns.

With these advantages in mind, in this thesis, we propose to utilize neural networks to forecast UE mobility which aids carriers in adjusting base station bandwidth based on the number of users using that base station. Practically, mobility prediction algorithms, such as neural networks, enable telecom operators to maximize network resources, reduce costs, improve QoS, and ultimately offer users a seamless and effective mobile experience. Thus, by enabling networks to become smarter, more responsive, and better suited to manage the needs of an ever-increasing number of connected devices and applications via predictive models, we aim to address gaps observed in the current resource allocation approach of Ethio-Telecom.

1.3 Objective

1.3.1 General Objective

To find suitable deep learning models that can forecast UE movement patterns based on historical patterns saved in CDR.

1.3.2 Specific Objective

- The below objectives are formulated to achieve the aim.
  - Neural network for time series forecasting knowledge acquisition
  - Determining the appropriate algorithms
  - Examining the outcomes of the model
  - Using the suggested system, analyze the acquired dataset

1.4 Scope and limitations

The scope of this research is to predict user mobility supported by neural network. Different method will be applied in this proposal through analysis and reviewing different type of literature to solve the problem of user mobility as well as quality service of the system by predicting it in competent manner. However, we acknowledge the following limitations observed in this thesis:

- The datasets provided by ethiotelecom for this has to be cleaned up due to a range of missing points.
- This approach followed in this thesis does not address holiday impacts, events and seasonal occation which are a crucial component in predicting consumer movement.

1.5 Contribution

By gradually locating cells and informing them of the capacity that is available in case of demand or user migration to that cell, the results of this research give Ethio telecom's significant insight. This is done by using a neural network and user mobility prediction as input. This research user Mobility Prediction method using deep learning with the following contributions:

- How the neural network helps estimate the best cell for a user's next location. Describe how this dynamic cell allocation benefits the user experience and reduces congestion.
- A method for neural network based User Mobility Prediction method.
- To emphasize how customers of Ethiotelecom could benefit from higher service quality due to this strategy. The telecom provider may provide seamless and unbroken connectivity by precisely forecasting user movements and maximizing capacity.
- Base stations and associated network hardware are major energy consumers in wireless networks. In places where there are no users, equipment can be turned off or its power reduced with the help of user mobility prediction, resulting in significant energy savings and cost savings.
- To build user mobility prediction system which assess the performance of the system compare to other article.

  User mobility prediction lowers waste, maximizes resource utilization in each of these scenarios, enabling firms to allocate resources more wisely, resulting in cost savings and operational efficiencies.

1.6 Literature Review

In order to increase customer satisfaction and lower paging costs for telecom providers, the project tries to forecast user mobility using deep learning algorithms. Through a survey of the literature, the study looks at appropriate deep learning algorithms and then does an experiment to evaluate the selected methods. RNN, LSTM, and variations of LSTM are suitable deep learning algorithms for predicting user mobility, according to the results of the literature review. Utilizing accuracy criteria, the models are compared, and the experiment demonstrates that the individual model outperforms the global model in forecasting user movement. As a result, the research comes to the conclusion that the individual model is the best method for predicting user mobility[14].

According on an individual's movement patterns throughout time and their most recent visited areas, the paper referenced in the question attempts to anticipate where they will be in the future. The authors create a unique algorithm for predicting the next destination based on this mobility model, called n-MMC, by extending the Mobility Markov Chain (MMC) mobility model to include the n previously visited places. As soon as n = 2, the algorithm performs with an accuracy for the prediction of the next position in the range of 70% to 95%, according to the evaluation of the algorithm on three separate datasets. This research may have applications in the evaluation of geo-privacy methods, the creation of location-based services that anticipate a user's future move, and the planning of proactive resource migration that is location aware According on the previously visited places, the author of the article [15] uses a mobility Markov chain model to forecast the user's future location. The author proposed the n- Mixed Markov Model (n-MMC) algorithm, which keeps track of the user's prior location data over n places. To reduce location prediction issues, several researchers undertook numerous sorts of research and investigations.Using mobility, anticipate the next location Based on their mobility patterns throughout time, Markov chains are a method for predicting a person's next position. The mobility behavior of the person is modeled using Markov Chains, where the current location is used to anticipate the next one before moving to the next. Numerous applications, including location-based services, traffic forecasting, and urban planning, can benefit from this method. The n prior visited sites might be taken into account to increase forecast accuracy. The algorithm created for this method is cutting-edge and highly accurate at predicting a person's next location[15].

The mixed Markov-chain model (MMM) has a method for forecasting pedestrian movement called pedestrian-movement prediction based on MMM. The MMM considers the personality of a pedestrian as well as how the environment affects their mobility. With a prediction rate of 56.8%, this technique has been used to analyze pedestrian trajectory data. The movement of pedestrians in a certain location can be modeled using a Markov chain[16].

The task of "next location prediction" involves predicting a person's next location based on their past locations. Using deep learning models that take contextual features into account is one method for completing this objective. A deep learning-based model for predicting the future site was proposed by Xiaoliang F. et al., which models contextual variables among trajectories, such as periodic patterns and dynamic trajectory data, and mines similarity between potential destinations. For the purpose of predicting the next location, A. Sassi et al. suggested a model that makes use of deep convolutional neural networks with location embedding. Another recent method predicts the next location using transformer decoder-based neural networks based on previous locations and travel mode data. These deep learning algorithms use contextual data and massive location history datasets to increase the precision of next location prediction[17].

The authors of the study [18] developed a Time-series Forecasting- Recurrent Neural Networks (STF-RNN) model that uses a recurrent neural network to predict people's future whereabouts. The suggested recurrent model incorporates time and spatial interval sequences that are utilized to identify long-term relationships and assist the existing model perform more effectively. For forecasting people's subsequent movements using mobility data, the study's authors presented a novel model known as Space Time Features-based Recurrent Neural Network (STF-RNN). The STF-RNN model incorporates time and spatial interval sequences that are used to discover long-term relationships and help the current model function more efficiently in order to forecast people's future whereabouts1. The movement of individuals is controlled by both their current location and past moves, according to the model's underlying tenet. The STF-RNN model was created to forecast people's future locations based on their present position, past movements, and additional variables like the time of day, day of the week, and weather.The model may be used to forecast people's future movements with high accuracy because it was trained on a big collection of mobility data. Numerous applications, including traffic management, city planning, and location-based advertising, are possible for the STF-RNN model.

Due of the complex traffic network, predicting mobility via machine learning algorithms is a difficult task. However, a number of modern technologies have been introduced for predicting mobility. To determine the optimal approach for mobility prediction in mobile networks and the performance of each machine learning (ML) model based on the mobility model, mobile users' future locations are predicted. Extreme Gradient Boosting Trees (XGBoost), Semi-Markov, and Support Vector Machine (SVM) are four mobility predictors that were compared in order to determine which was the most effective. XGBoost was found to have a relatively high predictive accuracy and a short execution time[19].

Using a deep learning algorithm, mobility prediction in wireless networks focuses on forecasting the movements of various objects, including cars, animals, typhoons, and visitors in a wireless environment. The objective is to deliver an accurate and adaptive positioning system to enhance network resource management and forecast the future location of mobile nodes. The type of deep learning algorithms used for wireless network mobility prediction is extreme learning machines and deep neural networks. These algorithms are renowned for their capacity to model and forecast the mobility of any given node in a mobile ad hoc network, as well as their universal approximation[20].

An extensive analysis of deep learning solutions for different mobility tasks was provided by the results of a survey on deep learning for human mobility. The study of human mobility is important because it affects numerous areas of society, including the spread of disease, urban planning, well-being, pollution, and more. Deep learning has been used to human mobility as a result of the availability of digital mobility data, including call records, GPS location information, and social media posts, as well as the predictive power of artificial intelligence. A taxonomy of mobility tasks is provided, along with a discussion of the difficulties involved with each task and how deep learning might be able to get around some of the drawbacks of conventional models. The survey looks at the top deep learning solutions for crowd flow prediction, next location prediction, and trajectory generation[21]

1.7 Methodology

The many procedural processes for this research proposal will be completed. First, a review of the literature on the most recent developments in deep learning-supported user movement prediction will be done. The most effective historical techniques for making accurate predictions will then be looked at. We will outline a novel approach for better user mobility prediction based on the state of the art. The new strategy will then be put to the test in an experiment, with the results being examined. Lastly, contrast the novel outcome with more traditional state-of-the-art techniques.

In Figure **??**, the suggested design of the system is illustrated, starting with dataset collection. A dataset is chosen for training and testing.

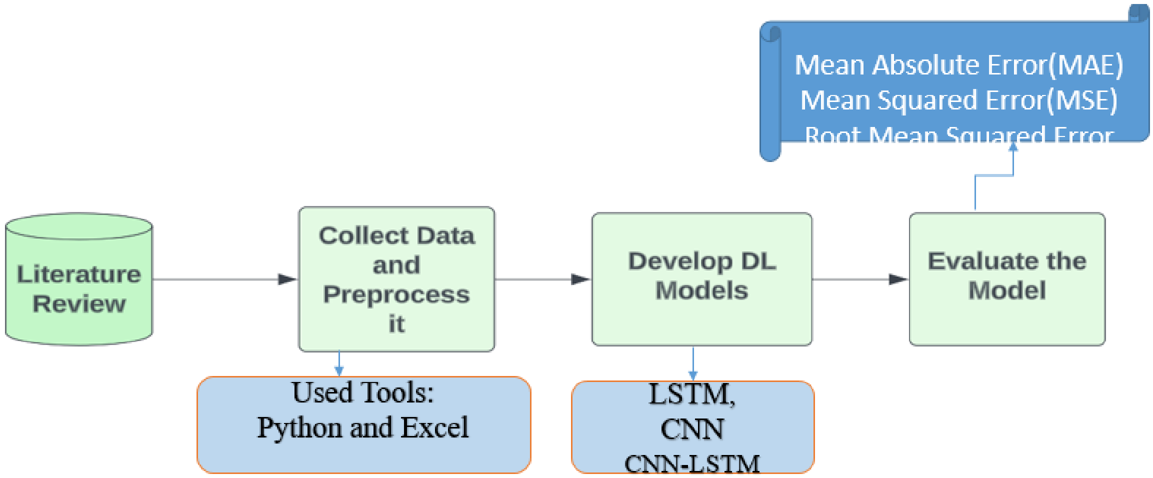

Figure 1.1: Research Methodology

The data preparation will be the end of data processing which can lead the data to be used by a deep learning model. Then the next step is the training of model to utilizing each of the datasets. The system is currently prepared for testing and performance analysis.

1.8 Thesis Outline

Rest of the paper is organized as follows:

- In Chapter 2, we present User mobility in Wireless Communication and Deep Learning
- In Chapter 3, we present techniques in time series forecasting using Deep Learning.
- In Chapter 4, Models Evaluation parameter and data Preparation
- In Chapter 5, we present result and discussion
- In Chapter 6, we present our conclusion and future work

Chapter 2

User Mobility Prediction in Cellular Network

2.1 Introduction

Mobility analysis in cellular networks involves studying and understanding the movement patterns of users or devices within a cellular network. This analysis provides valuable insights into how users move between different geographical areas and how they interact with the network infrastructure. In order to forecast future mobility patterns, predictive models can be created by looking at previous movement data, accounting for regional landscape variables, and taking routine behavior into account[9].

In many applications, including mobile network optimization, location-based services, and resource management, predicting the next location of mobile users in wireless networks using deep neural networks is a difficult and crucial problem. Deep neural networks (DNNs) can be modified to address this issue and have demonstrated promising results in sequence prediction applications. Using deep neural networks, wireless network users' future locations can be predicted. With any number of potential departure times, one can predict someone's future travel arrangements using the deep learning-based model Deep Trip. [13, 21, 22].

Mobility prediction contributes to cellular communication's ongoing development:

1. Seamless Connectivity: Ensuring constant connectivity for mobile users is one of the main objectives of mobility prediction. Cellular networks can proactively manage handovers between cell towers or base stations by anticipating where users will be. This minimizes call disruptions and data interruptions by automatically switching connections for consumers as they pass through various service regions.

2. Resource Optimization: In cellular networks, effective resource allocation is essential. The efficient distribution of network resources, such as bandwidth and signal

intensity, is aided by mobility prediction. By dynamically allocating resources based on expected user locations, networks may avoid traffic jams and guarantee that users have access to the necessary bandwidth.

3. Load balancing: With the help of predictive algorithms, networks can distribute user load among many cell towers. Networks can allocate resources to places with higher user densities by forecasting movement patterns and user distribution, preventing overloads in certain areas and preserving a constant level of service quality.

4. Enhancement of Quality of Service (QoS): Mobility prediction is essential for raising QoS for cellular customers. Networks can prioritize resources for users in high-demand areas by anticipating their movements, ensuring that they receive a higher level of service. Less lost calls, less latency, and quicker data connections are the results of this.

5. Reduced Latency: Cellular communication latency can be greatly reduced via predictive models. By anticipating where users will be, networks can pre-fetch data or connect to adjacent network components, reducing down on the time it takes for data to travel across the network and reach users' devices.

6. Energy Efficiency:Mobility prediction for mobile devices is a blessing for power management. Devices can reduce their energy consumption by anticipating usage patterns and network handovers. In order to increase battery life, they can modify their connection settings based on expected movement.

7. Enhanced User Experience: Providing a great user experience is the ultimate goal of mobility prediction. Consistent call quality, quick data connections, and seamless switching between various network cells or technologies are all advantages for mobile consumers. Improvements in user satisfaction result from this.

8. Network Design: Mobility forecasting has a big impact on long-term network design. Network operators can decide where to deploy towers, expand infrastructure, and increase capacity by studying historical mobility data and using prediction algorithms. As a result, networks grow effectively, and investments are made at a reasonable cost.

Utilizing and enhancing mobility prediction also contributes to resource conservation and improved performance[9]. As mobile communication migrates to next-generation networks, an urgent desire for higher-quality services arises, generating new mobility management challenges. Utilizing and improving mobility prediction tools appear as critical approach for solving these problems.

Additionally mobility prediction is used in wireless networks to manage bandwidth resources and facilitate effective planning. Mobile and wireless networks use mobility prediction to execute efficient network resource management and forecast the user's future location[11, 12].

Due to its effects on a number of societal facets, including disease transmission, urban planning, well-being, pollution, and more, the study of human mobility is essential. Deep learning has been used to human mobility as a result of the abundance of digital mobility data, including call logs, GPS data, and social media posts, as well as the predictive power of artificial intelligence[21]. The primary benefit of mobility prediction is the ability to allocate in advance a feasible more access point (node) before. In order to reduce the interruption to communication between mobile terminals, the mobile terminal may leave the current one. Location varies by wireless network architecture; in infrastructure-based networks, location refers to the access point that the mobile node is connected to[11].

In a world that is becoming more networked, mobility prediction in wireless contexts is essential for the success of IoT applications. With their ability to recognize complex patterns, deep neural networks are a key component in creating precise and flexible location services for mobile devices. This project, meanwhile, is not without difficulties because it must take into account the complex behaviors of mobile users and the dynamic nature of wireless networks. However, the need for mobility prediction is encouraging interdisciplinary cooperation and finding application in a variety of disciplines, ultimately influencing our capacity to comprehend and manage our constantly changing digital environment[20].

In conclusion, the abundance of mobility data produced by mobile phones, including CDRs, network traffic, GPS, and Wi-Fi connections, is a goldmine of knowledge that provides light on large-scale human dynamics. Its benefits include lengthy coverage, cost-effectiveness, and the potential to advance industries as diverse as healthcare and urban planning. The knowledge gained from mobility data provided by mobile phones will be important for comprehending and improving our interconnected environment as the digital age progresses.

2.2 Machine Learning Basics

Without necessarily having been particularly built for that activity, a machine learning algorithm is given data and makes use of statistical techniques to "learn" how to get better at that task over time. ML algorithms, on the other hand, use historical data as input to forecast fresh output values. So, ML comprises of both supervised learning (where the expected output for the input is known because labeled data sets are used) and unsupervised learning (where the expected outputs are unknown because unlabeled data sets are used). Without necessarily having been particularly built for that activity, a machine learning algorithm is given data and makes use of statistical techniques to "learn" how to get better at that task over time. ML algorithms, on the other hand, use historical data as input to forecast new output values. So, ML comprises of both supervised learning (where the expected output for the input is known because labeled data sets are used) and unsupervised learning (where the expected outputs are unknown because unlabeled data sets are used) that task was programmed.

Machine learning is the process of letting artificial intelligence (AI) find solutions and new knowledge on its own. Artificial intelligence (AI) systems can utilize machine learning to analyze vast amounts of data, identify patterns, and make predictions or decisions on those patterns. Making machines smart by teaching them to learn, understand, and mimic human and animal behavior is the aim of the field of research known as artificial intelligence (AI)[23, 24, 25]. The branch of study known as artificial intelligence (AI) tries to make machines intelligent by training them to learn, think, and replicate the actions of people and other animals. The purpose of artificial intelligence (AI), a large field of computer science, is to create intelligent machines that can do activities that typically require human intelligence. The widespread acceptance of AI implies a willingness to use it to support human decision-making, as noted by Dalpiaz 2020 Requirements and Burns 2022 Artificial Intelligence. On the other hand, a subset of artificial intelligence known as machine learning (ML) uses mathematical formulas to understand, spot, and analyze data patterns[26, 27].

Decisions made by machine learning can be made with little to no human participation. Three categories of machine learning algorithms exist:

- **Supervised:** A labeled dataset is utilized in supervised learning techniques. This dataset contains the input data as well as the matching output or outcome. In order for the machine learning model to learn from the raw data and generate correct predictions going forward, the data must be labeled in order to give it context and meaning.

- **Unsupervised:** Unsupervised learning algorithms employ unlabeled data and look for a hidden structure or pattern to predict the data point to a given group. unsupervised learning enable users to carry out more complicated processing tasks. Nevertheless, compared to other natural learning processes, unsupervised learning can be more unpredictable.

- **Reinforcement learning:** In the reinforcement strategy, the agent can evaluate and engage with its surroundings, allowing it to act through trial and error based on input from its experiences. Reinforcement learning focuses on acting in a way that maximizes the reward in a given scenario [28]. In general, reinforcement methods entail assigning favorable penalties for desirable actions, which can shape and reinforce those actions over time. Agents can learn and develop through trial and error based on feedback from their experiences by analyzing and interacting with their surroundings.

2.3 DEEP LEARNING

Deep learning is a type of machine learning that processes inputs through a neural network design that was inspired by biological processes. The data is processed through a number of hidden layers in the neural networks, enabling the machine to learn "deeply," forming connections and weighing input for the optimal outcomes.

Deep Learning is a branch of machine learning that teaches computers to analyse data in an approach similar to how human intelligence does in order to gain insights and make decisions. Deep learning algorithms are also known as deep neural networks since they use the same design as neural networks[20]. It is a form of artificial intelligence that is based on how the human brain is organized and functions. However it is currently receiving attention and expanding quickly for the reasons listed below:

- **Massive data learning capacity:** It is easy for data analysts to gather, analyze, and understand data since deep learning algorithms can handle and analyze massive amounts of data with labelled.
- **Massive data learning capacity:** Deep learning algorithms may carry out more complex computations since they are built in a hierarchy of increasing complexity and abstraction
- **Success across a variety of fields:** Many industries, including computer vision, natural language processing, and gaming, have found success with deep learning

Deep learning systems for predicting user mobility have a number of benefits, such as:

- **Increased accuracy**: Deep learning algorithms have the capacity to handle huge amounts of data and find complex trends that can increase the precision of user mobility prediction
- **Improved quality of service:** In areas including wireless networks, traffic prediction, and urban planning, accurate user mobility prediction can help consumers receive higher-quality services
- **Reduced costs:** Through resource allocation optimization and a decrease in useless handovers in wireless networks, accurate user mobility prediction can aid in cost reduction
- **Flexibility:** Deep learning algorithms are flexible and adaptable to various domains since they can be trained on a variety of forms of data, such as phone records, GPS traces, and social media posts
- **Scalability:** Deep learning methods are scalable and suitable for real-time user mobility prediction since they can handle big datasets

Overall, the accuracy, reliability, and cost-effectiveness of many applications in wireless networks, traffic prediction, and urban planning can be enhanced by utilizing deep learning algorithms for user mobility prediction.

2.3.1 Neural Network

A neural network is described by Dr. Robert Hecht-Nielsen as a computing system made up of several densely interconnected processing components that may process data based on their dynamic state responses to outside inputs

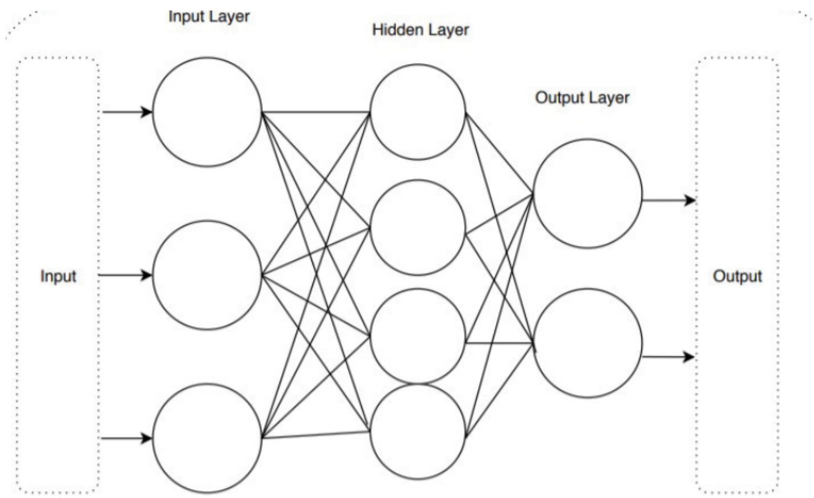

Figure 2.1: Architecture of neural

Input Layer: The input layer of a neural network is the first layer to receive input data and pass it on to subsequent layers. A feed-forward neural network has an input layer, one or more hidden layers where all the calculation takes place, and an output layer that generates the output for the inputs that are provided[29].

Hidden Layer: In a neural network, calculations are carried out in the hidden layer, and responses are then passed on to the higher layers. Before sending the input data to the output layer of a neural network, the hidden layer performs calculations and modifies the data. The activation functions and weighted connections that may be used in the hidden layer computations depend on the network design. Through experimentation and tuning, it is possible to identify the number of hidden layers and nodes[29].

Output Layer: The layer of a neural network that generates the outcome for a certain input is known as the output layer. It transmits the input data to the following tiers as the network's last layer. The type of prediction needed by the model determines the activation function used by the output layer, which is often different from that of the hidden layers. The output layer of a multilayer perceptron (MLP) generates the output variables. When there are numerous output classes or kinds, the predicted value or values constitute the output layer in a ResNet. The final fully connected layer and the final classification layer should be changed with new layers customized for the new data set, and the Output Size should be increased in order to retrain a pertained network to classify new images[29].

2.3.2 Long Short-Term Memory (LSTM)

An advanced recurrent neural network (RNN) is a network with long short-term memory. It has the ability to pick up on order dependence in sequence prediction. Due to the operation of backpropagation's vanishing gradient problem, RNN's fundamental drawback is its inability to learn long-term dependencies. In contrast to traditional RNN models, as illustrated in Figure 2.2, LSTM is capable of handling vanishing gradient issues with ease thanks to its four interacting layers within a cell. The gates in the LSTM structure either enable the value to be applied to the cell state or change the value by preventing the data from being applied, creating a cell state that runs across the entire LSTM. Additionally, there are elements known as gated cells that allow data from earlier LSTM or layer outputs to be stored in them. The LSTM is composed of three components: the input gate, the foregate gate, and the and Output gate[30, 31].

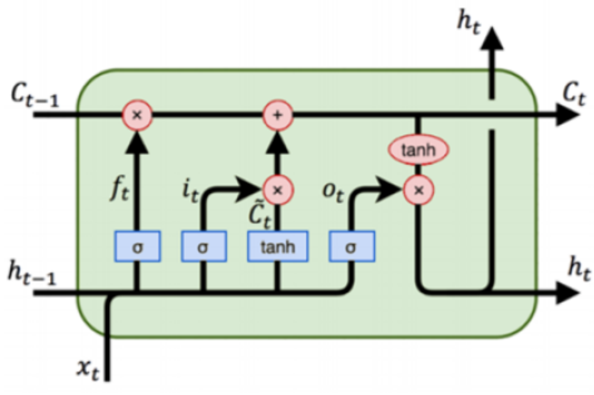

Figure 2.2: LSTM Architecture

The Forget gate: assesses if the data from the previous timestamp should be remembered or if it is unnecessary and should be ignored. Between the current input X_t and the hidden state H_{t-1}, information is transmitted via the sigmoid function. The following is the forget gate equation.

$$f_t = \sigma(X_t * U_f + H_{t-1} * W_f) \tag{2.1}$$

Where W_f is the weight matrix related to the hidden state and U_f is the weight related to the input.

Input gate: determines the relevance of the new information brought in by the input. The previous hidden state and the present input are first combined using a sigmoid function. Determines which values will be updated by adjusting the values to be between 0 and 1. The equation for an input gate is given in Equation below.

$$i_t = \sigma(X_t * U_i + H_{t-1} * W_i) \tag{2.2}$$

This is an input gate, and U_i is the input weight matrix.

When *tanh* is used as the activation function, the new information is a function of the input x at time stamp t and a hidden state at time stamp $t-1$. Due to the *tanh* function, the value of new information will lie between -1 and 1. The status of the cell is as follows at this time stamp C_t:

$$C_t = f_t * C_{t-1} + i_t * \tanh(x_t * U_c + H_{t-1} * W_c) \tag{2.3}$$

Output Gate: The cell transmits the newly updated data from the present timestamp to the following timestamp

$$O_t = \sigma(X_t * U_o + H_{t-1} * W_o) \tag{2.4}$$

The current hidden state is determined by the modified cell states O_t and $tanh$. as shown in the following equation.

$$H_t = O_t * \tanh(C_t) \tag{2.5}$$

It comes out that the long term memory C_t and current output Ct are functions of the hidden state (Ht).

2.3.3 Convolution Neural Network (CNN)

A deep neural network called a CNN was initially developed to solve image processing issues. It is now used with data that can be displayed as a grid-like matrix. For instance, a 1D vector can be used to represent time series and textual data, and a 2D matrix can be used to represent the pixels in image data. The term "convolution neural networks" was given to the architecture in honor of the mathematical function Convolution. On at least one of the neural networks, a linear operation is carried out in a typical matrix multiplication[32].

There are input, hidden, and output layers in CNN. A CNN model is created using the convolutional layer, pooling layer, and fully connected layer as its three main building blocks. A convolution layer's primary function is to identify and extract characteristics from the input. Multiple convolution kernels (filters) are employed in each convolution layer to convolve the input feature map in order to create the output feature map. The pooling layer, sometimes referred to as the subsampling layer, is used to lessen the feature map's dimensionality. In order to prevent overfitting, it also lowers the amount of parameters in the network. Finally, whether for classification or prediction, the fully connected layer flattens the output of a conventional neural network and then generates the appropriate output[33].

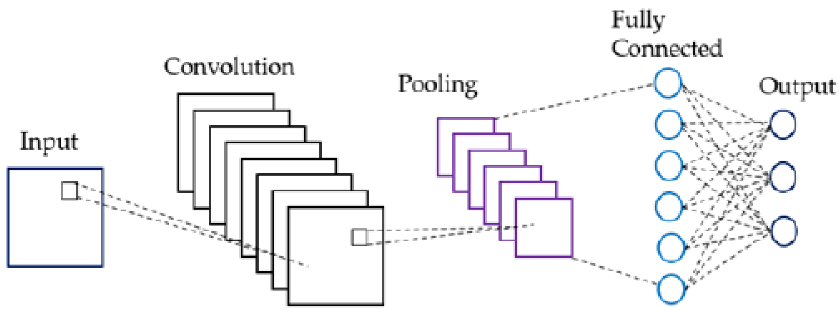

Figure 2.3: CNN Architecture
[34]

To extract information along the time dimension, use CNN 1D convolutions. A convolution can be thought of as putting a filter on top of the time series and moving it around. In contrast to photographs, which display two dimensions (width and height), filters only display one dimension (time). The filter can alternatively be thought of as a general-purpose non-linear time series transformation.

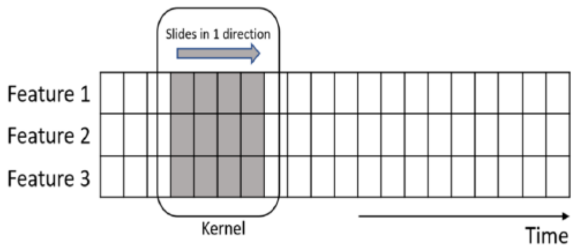

Figure 2.4: 1D CNN for Time Series Data
[34]

2.3.4 CNN-LSTM Model

A CNN-LSTM combines a convolutional neural network, which excels at processing one-dimensional data, with a long short-term memory, which excels at identifying and learning long-term dependencies. Convolutional, Max pooling, sequential, and linear decoder layers make up CNN-LSTM. The architecture diagram below depicts the layers mentioned: Convolutional neural network and regression models are outperformed by the CNN-LSTM model. Given that it is a hybrid technique, it is used in models with longer dependencies and connected predictions.

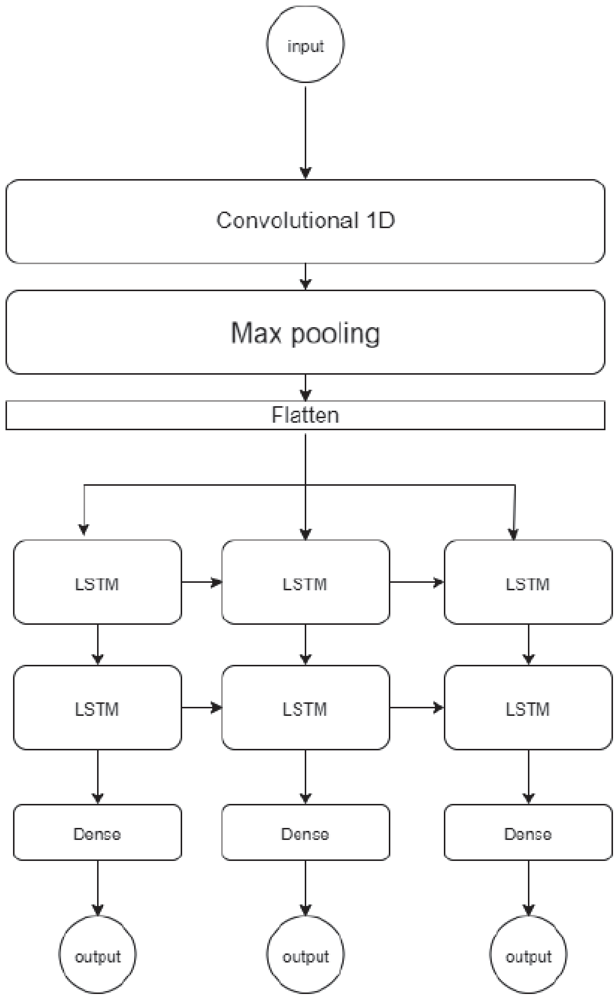

Figure 2.5: CNN-LSTM Architecture
[14]

The CNN model can automatically recognize and extract features from raw sequence data. This feature of the CNN model can be combined with the LSTM model. More effectively capturing both long- and short-term reliance of temporal information is the LSTM network. While the LSTM model coupled in tandem analyzes and produces an output, the CNN model accepts input data sequences and extracts relevant feature information.

Chapter 3

Time series Forecasting by Deep Learning

3.1 Introduction

A technique for forecasting time series is the use of historical data to make predictions about the future. It entails creating models through historical study, using them to draw conclusions and guide strategic decision-making in the future. Time series analysis is the process of obtaining insightful summaries and statistical data from points that are arranged in time.

Time series data: A time series is a collection of data points gathered over a period of time that enables us to track changes over time. The time units and a numerical value for each time unit are the two main components of the data points in time series data, which are gathered at regular intervals of time. Any variable that evolves over time can provide time series data. In general, time series data is used in any area of applied science and engineering that uses temporal measurements, including statistics, signal processing, pattern recognition, econometrics, mathematical finance, weather forecasting, earthquake prediction, electroencephalography, control engineering, astronomy, and communications engineering.

A particular method of examining a set of data points gathered over a period of time is called a "time series analysis." Analysts record data and examine it to look for patterns or trends in time series analysis. Stock time series data and flow time series data are the two basic categories into which time series data may be divided. Stock time series data refers to measuring characteristics at a specific moment, much like a static image of the data as it was. Measurement of attribute activity over a specific time period, which often constitutes a percentage of the results and is referred to as flow time series data, is what is meant by this term. In time series data, variations might appear irregularly all across the data.

The analysis of how variables change over time uses time series data. It offers an additional source of data as well as a predetermined order of data dependencies. To track the evolution of a certain asset, security, or economic characteristic over time, time series data might be helpful. It can also be used to compare the changes related to the selected data point to changes in other variables over the same time frame. Time series are also employed in a number of non-financial applications, including ectroencephalography, weather forecasting, and earthquake prediction.

In general, time series data analysis is an effective tool that can be used to examine and make predictions about a variety of variables in a variety of industries.

A time series is a group of observations arranged sequentially that may be used to study and predict the values of the future. Time series data has the benefit of giving the researcher the information they need without imposing any minimum or maximum time constraints on the data collection process. As a result, time series data are used extensively across many businesses because they enable the prediction of future values using information that has already been gathered (past values). Today, corporations and scholars use time series analysis and forecasting more than any other quantitative method. The following are some of the main benefits of time series analysis:

- **Helps find Patterns:** Time series analysis enables the finding of trends and patterns in data that may not have been apparent. This may help firms in making wise decisions and acting appropriately.

- **Enhances data cleaning:** In order to identify the true "signal" in a data collection, time series analysis can assist clean the data by removing outliers and noise.

- **Supports in data understanding:** By understanding the basic significance of the data using different models, time series analysis can assist analysts better understand a data collection.

Overall, time series analysis is a strong tool that helps organizations and researchers examine and predict future values using data that has already been gathered. Time series data can be employed for forecasting, which is the process of anticipating future data based on historical data.

Univariate and multivariate time series data are the two forms of time series data that are classified.

- **Univariate time series Data:** is a term used to describe a type of time series data where there is only one variable that changes over time. One example of a univariate time series is information obtained from a sensor that continuously records a room's temperature.

- **multivariate time series Data:** a type of time series data that has multiple variables that change over time. A multivariate time series is, for instance, information gathered from various sensors throughout time that measure the temperature, humidity, and pressure of a room.

Essentially stated that the number of variables that change over time distinguishes univariate from multivariate time series. Multivariate time series have more than one variable, while univariate time series have just one.

In order to forecast future values, it includes studying time-stamped data points to find trends and patterns that may subsequently be extrapolated. One-step ahead forecasting and multi-step ahead forecasting are the two categories under which time series forecasting is categorized.

- **One-step forecasting:** Predicting the following value in a time series based on the prior values is known as one-step forecasting. When attempting to foresee short-term changes in a time series, this method of forecasting is beneficial. Predictions about the stock price for the following day or the energy demand for the following hour are two examples of one-step forward forecasting.

- **Multi-step forecasting:** Multiple future values in a time series are predicted using multi-step forward forecasting. When attempting to foresee long-term changes in a time series, this method of forecasting is beneficial. Predictions of sales for the following month or weather patterns for the following year are two examples of multi-step ahead forecasting.

In summary, time series forecasting is an effective technique for making predictions about the future based on the past. Several models are available to pick from depending on the particular time series being investigated and the forecasting objective. It is divided into one-step ahead forecasting and multi-step ahead forecasting.

Time series forecasting is a method for predicting future values across time or at a single point in the future by using historical and present data. It entails creating models through historical study, using them to reach conclusions and inform strategic decisions in the future. Numerous academic disciplines, including corporate planning, control engineering, earthquake prediction, econometrics, mathematical finance, pattern recognition, resource allocation, signal processing, and more, use time series forecasting in a variety of contexts. Forecasting the weather, sales figures, stock prices, and price movements for cryptocurrencies like Bitcoin and Ethereum are some common applications of time series forecasting.There are numerous forecasting methods, such as Autoregressive Moving Average (ARMA), a statistical model that forecasts future values based on historical data. Convolutional and Recurrent Neural Networks (CNNs and RNNs) are further methods. The best forecasting technique must be chosen for the particular application because each method has advantages and disadvantages[35, 36, 37].

Analysts begin with a historical time series and look for patterns of time breakdown, such as trends, seasonal patterns, cyclic patterns, and regularity5, before performing time series forecasting. Time series data models come in a variety of shapes and can depict various stochastic processes[38].

Overall, time series forecasting is a typical task that many data scientists should be familiar with because it can offer insightful information for making strategic decisions across a range of subject areas[39].

3.2 Timeseries Forecasting with LSTM Model

LSTM models are highly useful when working with data that has temporal patterns and dependencies. The LSTM recurrent neural network architecture has been widely utilized for time series forecasting. Since it can spot long-term dependencies in sequential data, it is suitable for assessing time series data[40]. They can handle data with recurrent local patterns and low granularity. Real-time prediction is made easier by the ability of LSTM models to transmit states between sessions. .

Essentially, LSTM models provide benefits that make them suited for time series forecasting, including the ability to capture long-term dependencies and handle sequential data. They are more sophisticated than conventional models, can be difficult to comprehend, and call for thorough hyperparameter modification.

3.3 Time series forecasting with CNN Model

In addition to image identification, CNNs can be used for time series forecasting.To more effectively recognize local and temporal patterns in the data, convolutional layers can be added to LSTM models. Dilated convolutions offered by CNNs help the network understand the relationships between multiple observations in the time series. Researchers have experimented with combining CNNs with autoregressive models and other techniques to improve prediction performance[40, 41]

3.4 Time series Forecasting with CNN-LSTM Model

Whether to use an LSTM or CNN model for time series forecasting relies on the specific data and problem you are attempting to solve[20]. Use an LSTM model if the data has low granularity and recurrent local patterns if a simple model is appropriate and won't cause overfitting. Convolutional layers can be added to an LSTM model to help it capture local, temporal patterns in the data. In some cases, CNN-LSTM models have been shown to outperform both CNN and LSTM models.

Time series forecasting may be done using both LSTM CNN-LSTM and CNN models. While CNN models can collect local information, temporal patterns in the data, LSTM models can handling data with temporal patterns and capturing long-term dependencies. CNN layers can be added to LSTM models to improve predictions even further. The precise properties of the data and the issue at hand determine to use LSTM CNN-LSTM or CNN.

Chapter 4

Models Evaluation Parameter and Data Preparation

The experiment's model and tools are clearly defined and presented in this chapter, along with a brief discussion of the duties involved in data preparation. As part of the data preparation, the metrics used to assess the performance of the model are also explained.

4.1 DATA-SETS

The dataset employed in this study is the result of a comprehensive data compilation process that draws from two distinct departments: the Department of Communication and Fraud Security and the Department of Radio Access Network (RAN) Wireless Engineering. The amalgamation of data from these two sources is an integral step in the research process, and the subsequent dataset is constructed as follows:

- Data Sources: The primary data sources include Call Detail Record (CDR) data obtained from the Department of Communication and Fraud Security and dataset parameters derived from the Department of RAN Wireless Engineering. These two departments provide critical insights and information related to telecommunications and network operations.

- Merging Based on Cell ID: To create a unified dataset that encapsulates relevant information from both departments, the data is merged based on Cell ID. Cell ID is a fundamental identifier in mobile networks, and merging the data using this parameter ensures that the dataset is structured around cellular network locations.

- Seven-Day Study Period: The data collection phase spans a period of seven days. This duration is selected purposefully to capture a representative snapshot of user behavior, network activity, and potential variations over time of june 6, 2023 to 12, 2023 sequential of 7 days.

- User Identity Encryption: In adherence to stringent data security and privacy protocols, the user identities present in the CDR data are encrypted before transfer to the researcher. This encryption practice safeguards sensitive user information and aligns with established data protection regulations.

CDR dataset has a lot of features, but only a few are displayed in the Table 4.1.

Table 4.1: Selected CDR dataset

Timestamp	Cell Id	Service No
2023-06-05 22:58:24	1	102
2023-06-05 23:20:09	2	70
2023-06-05 23:59:34	3	80

Table 4.2: Selected Dataset parameter

Cell Id	Latitude	Longitude	Site ID
1	9.1392	38.78733	113300
2	9.1392	38.78733	113300
3	9.1392	38.78733	113300

The dataset from the Department of RAN (Radio Access Network) Wireless Engineering was collected from 200 sites near Megenagna. This dataset contains a multitude of features that were carefully selected to represent various aspects of the wireless network and user activity. While the dataset is extensive, for clarity and focus, only a subset of the most relevant features is presented in Table 4.2. and selected location and site distribution is represented as Figure 4.1. These selected features are crucial for modeling and understanding the performance of the wireless network and its interaction with user mobility. They provide valuable insights into network utilization, signal quality, and user behavior.

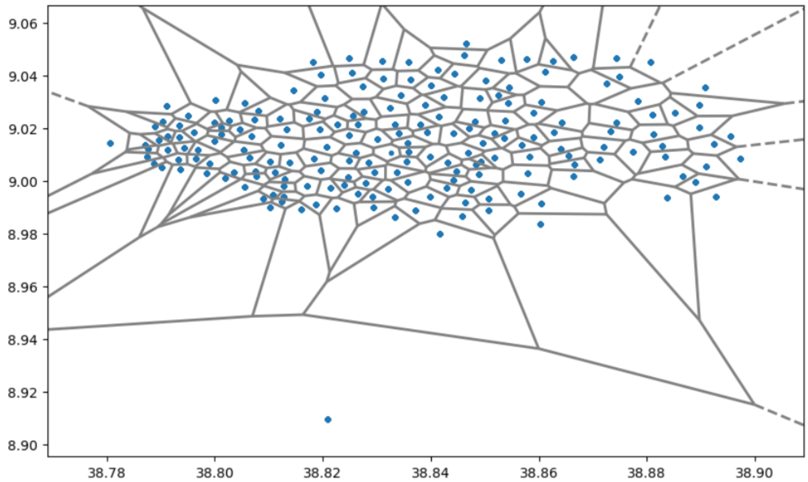

Figure 4.1: Cells Visualization

So, file splitting and parsing tools in the python environment, like fsplit and xml2csv are used to get manageable data in the appropriate format for the tools (sklearn).

4.2 Data Preprocessing

When creating a model, data preparation includes data selection and data preprocessing. The most important of these data preparation jobs is data preprocessing because the majority of real-world data are incompatible, incomplete, and contain mistakes and missing values. The accuracy and effectiveness of the generated data model are increased due to data preparation procedures, which also help to improve the quality of the data. This case explains the data preparation strategy that was employed in the study. By representing user mobility of service no 65037 in Figure 4.2

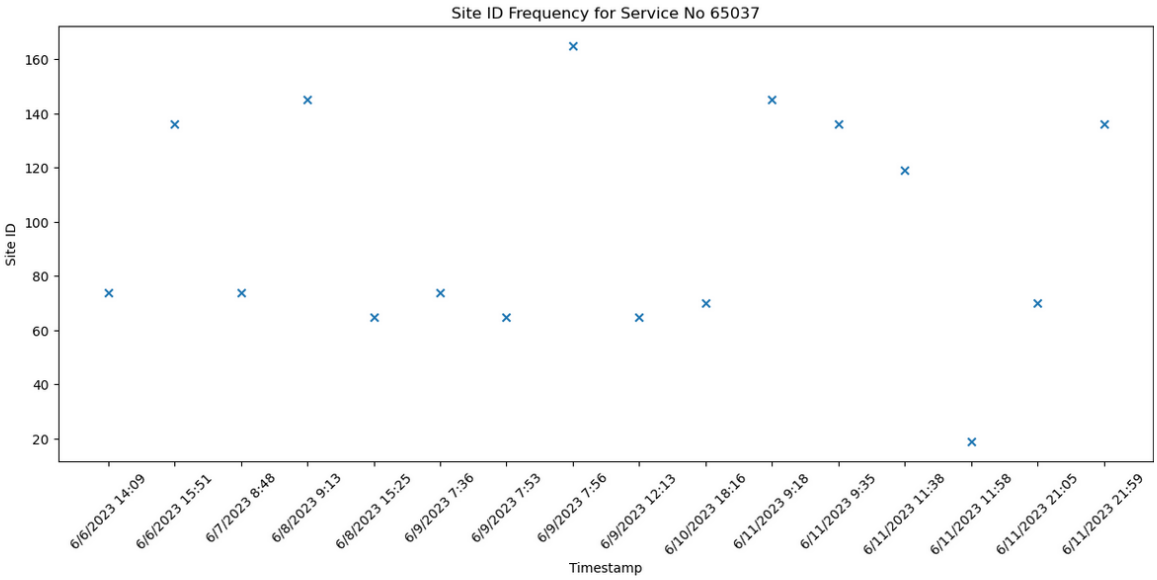

Figure 4.2: Visual representation of Service No

The plotted graph in Figure 4.2 shows a user mobility scenario. The total number of time slots is on the X-axis, while cell id is on the Y-axis. The user identities used as examples are from the CDR data set. The data with the chosen features is once more analyzed and turned into a timestamp. Due to the possibility that the service number may not always be linked to the network, this data contains several missing data points. It is example of user mobility with X-axis represent Time and Y- axis representing site id.

4.2.1 Data Selection:

The required features for the time series must be chosen once the raw data has been collected from the server and has been examined. The dataset for this study was compiled using data from 200 sites provided by the RAN Wireless and Network Planning Department and the Communication and Fraud Department of ethiotelecom. Multivariate features from the CDR dataset include timestamps, user identities, cell IDs, and the dataset parameter. Cell ID, site Id, Latitude and Longitude are contained in the dataset parameter infrastructure.

4.2.2 Dataset Split and Model Evaluation

The dataset for this study is split into a training set, and a validation set. Using a "walk-forward" validation method, the model's performance on time-series data is assessed.The training dataset is used to identify the ideal hyperparameter values during the model training procedure. This makes sure that the model is properly adjusted for the unique properties of the time-series data, which is important for making precise predictions.

After the model was constructed, it was tested against a validation data set to see if it was overfitting, underfitting, or a good fit. When a model performs well on training data but poorly on test data, this is known as overfitting. The model learns every detail, hence it is unable to generalize to the unknown dataset. Due to its inability to accurately represent the link between input and output values, underfitting causes the model to have high training and high test error. When there is a strong match, the model performs well for both the training and test data sets.

Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Squared Error (MSE) are the most often used performance evaluation metrics for regression models. The formulas for the evaluation measures employed in this work, RMSE,MAE and MSE, are as follows:

Mean Squared Error (MSE):average squared deviation between the expected and actual values.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \tag{4.1}$$

where N is the number of data points, and y_i and $(\hat{y}_i)$ are the actual and predicted values, respectively.

Mean Absolute Error (MAE): calculates the difference between the actual and predicted amounts in absolute terms.

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i| \tag{4.2}$$

Root Mean Squared Error (RMSE)

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{4.3}$$

4.3 Model Configuration

The most hyperparameters considered in our models are learning rate, Number of Layers and Units, activation functions, dropout, batch-size and epoch.

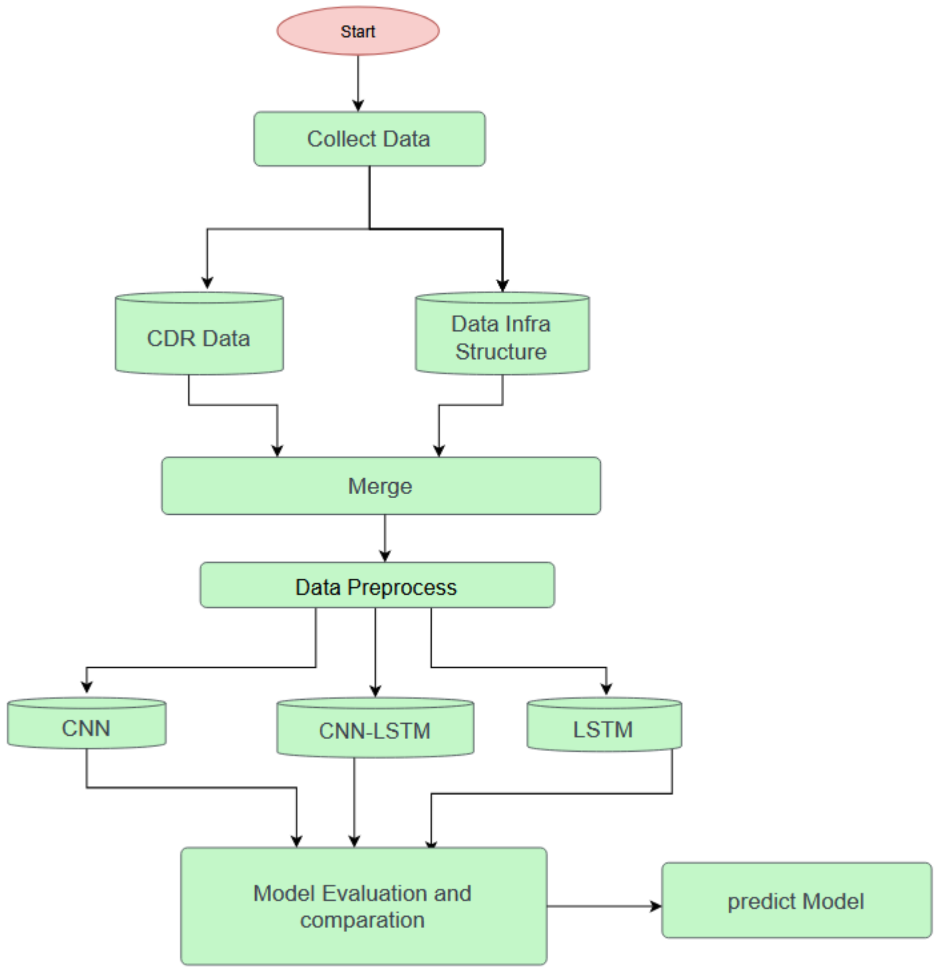

Figure 4.3: System Model

The model is trained with those optimal parameters in methodology section using a training dataset, and the performance of the model is evaluated with a test dataset. The algorithm analysis is done in above Figure **??** block diagram steps.
The LSTM, CNN, and CNN-LSTM models are suggested in this study to address the regression issue for time series problems. Before training a model, hyperparameter variables should be initialized during model development to find the model's ideal setup. There are a few hyperparameters such as optimizer type, loss function, and activation function.

Loss function: MSE was utilized in this study as the loss function because it is the most used loss function for regression issues and minimizes the differences between real and predicted values.

Optimizer: The model is updated by an optimizer in response to the loss function. Due to the Adam optimizer's efficiency in terms of computing, memory requirements, and usage of adaptive learning rates, which aid in quick convergence, it is utilized for stochastic gradient optimization.

Activation function: Regression or classification issues, as well as other deep learning network types like RNN and CNN, are used to determine the kind of activation function to use. Convolutional neural networks should use the ReLU activation function, while LSTM networks should use the sigmoid activation function. ReLU, linear are for CNN model and CNN-LSTM model and Relu and sigmoid are utilized for LSTM models in this study.

Learning Rate: The models are tuned through learning. It updates network weights to reduce error. Model performance would suffer if the learning rate was set too low or too high. A low learning rate will result in delayed network weight updates and slow training, whereas a high learning rate will result in divergent error behavior.

Epoch: The number of epochs corresponds to the amount of iterations through the training set of data. The training sample may modify the internal parameters of the model at each epoch.

Batch-Size: The number of training samples sent to the networks in a batch. One or more batches can be created from a training dataset. The number of training examples used in one forward and backward pass (or one iteration) through the neural network during training is referred to as the batch size. It regulates how many training instances are processed at once before the model's weights are updated. A smaller batch size indicates more regular updates, whereas a bigger batch size indicates fewer frequent updates. The most common batch sizes in regression is between 2 and 32.

Dropout: is an approach to regularization. To make the neural network, some nodes must be removed. A certain number of layer outputs are dropped at random during training.

Additionally, various parameters, such as batch size, filter size, kernel size, stride value, size of Max pooling layer, and epoch, are specifically chosen to capture the time series of the data. The values of these parameters are shown in Table below.

Table 4.3: Hyperparameters Used in LSTM Model

Hyperparameters	Values
Hidden Layer	64
Hidden layer Neurons	Layer1 16 layer2 16
Batch size	64
Dropout	0.7
Optimizer	Adam
Activation	(ReLU) and Sigmoid
Epoch	10

The values for the other hyperparameters are shown in the table below and were chosen based on the suggested values. For instance, to reduce the processing time required for the convolutional operation, the number of filters in the convolutional layers should be expressed as a time series.

Table 4.4: Hyperparameters Used in CNN Model

Hyperparameters	Values
Filter size	16 and 8
Kernel size	1
Batch size	16
Loss	MSE
Optimizer	Adam
Activation	(ReLU) and Linear
Epoch	10

Table 4.5: Hyperparameters Used in CNN-LSTM Model

Hyperparameters	Values
Hidden Layer	2
Hidden layer Neurons	Layer1 16 layer2 4
Batch size	16
Dropout	0.5
Optimizer	Adam
Activation	(ReLU) and Linear
Epoch	10

Chapter 5

Results and Discussion

5.1 Introduction

To get the required model fit, the hyperparameters can be modified by examining these scenarios. The process of parameter tuning is essential to the creation of deep learning models. To make sure a model works well with unknown data, hyperparameters must be chosen, optimized, and evaluated. The right parameter adjustment can result in models that generalize well and provide reliable predictions.

Throughout parameter adjustment the Model evaluation is essential to monitor how well the model matches the training set of data. If the model is underfitting, it is too simple to detect the fundamental trends in the data. Because the model is extremely complex when it is overfitting, it fits noise in the data rather than the actual patterns. If a model is good fit, the training and validation data fit the model well in terms of generalization.

The data collection is modeled as a time series of sequential data, and it is believed that the model construction would capture all of its properties and elements. The model is created for an LSTM, CNN and CNN-LSTM algorithms are employed.

Parameter tuning is performed for some hyper parameters to obtain a better result. The model was checked whether it is overfitting, under fitting, or a good fit before the final evaluation of the model with the test set.

5.2 LSTM Loss

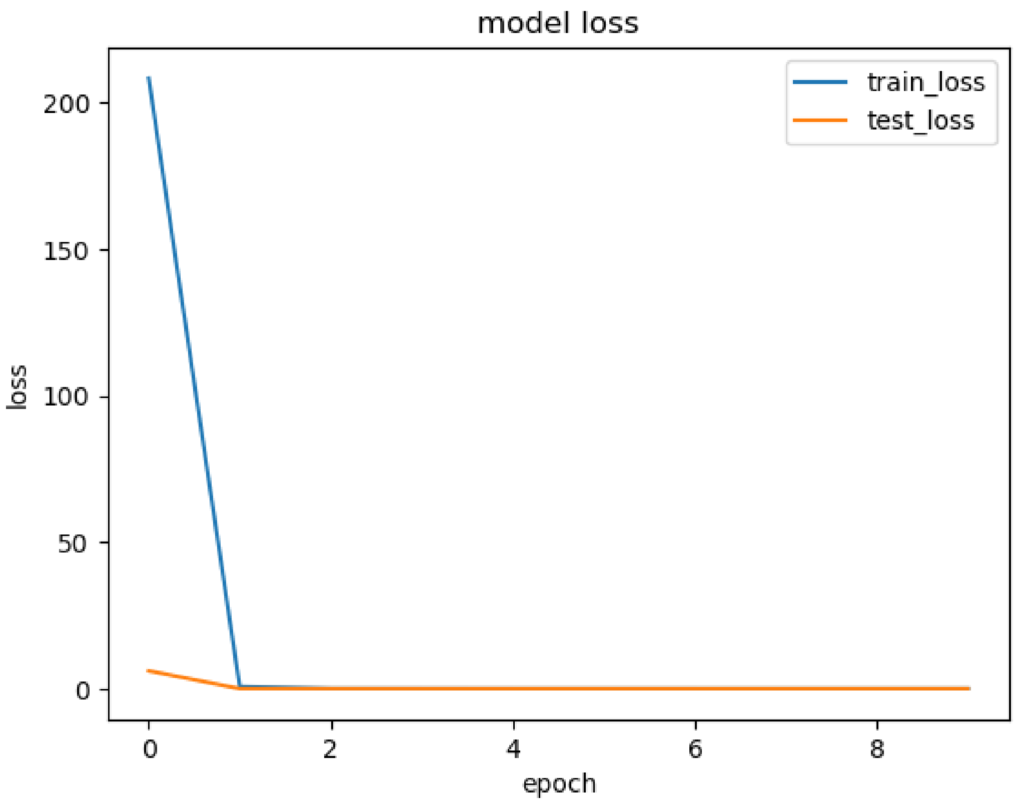

Figure 5.1: LSTM Loss

Figure 5.1 above illustrates the comparison of training and validation error against the number of epochs, and about 10 epochs, the MSE becomes more approach to zero and the same for both training and validation datasets. It indicates that the model is well fitted and ready to evaluate with the test dataset, specifically when epoch is above 1.

5.3 CNN Loss

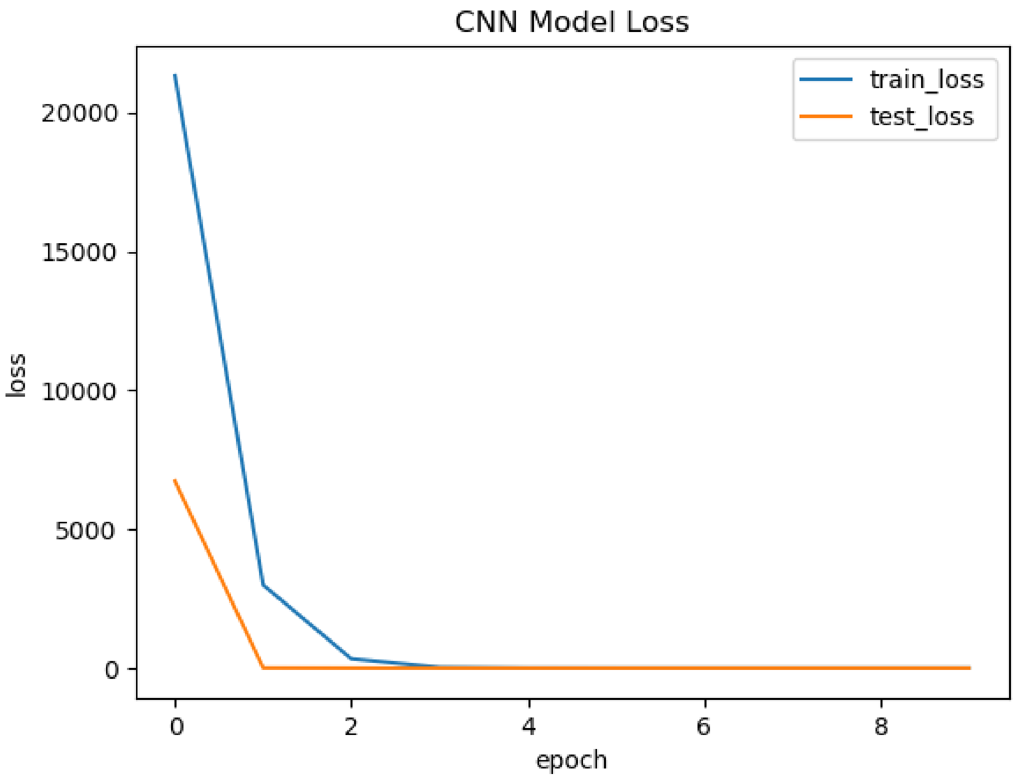

Figure 5.2: CNN Loss

Corresponding to the result in Figure 5.2, the MSE becomes more approach to zero and the same for both training and test datasets. It indicates that the model is well fitted and ready to evaluate with the test dataset, specifically when epoch is above 3, it indicates that the model is well fitted.

5.4 CNN-LSTM Loss

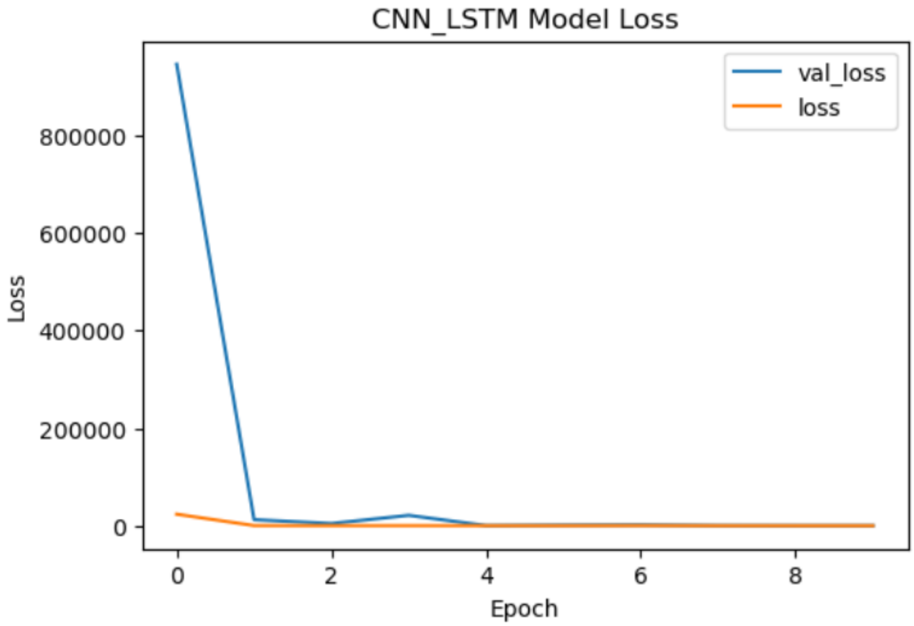

Figure 5.3: CNN-LSTM Loss

Corresponding to the results in Figure 5.1, 5.2 the MSE becomes more approach to zero and the same for both training and test datasets. It indicates that the model is well fitted and ready to evaluate with the test dataset, specifically when epoch is above 3.5, it indicates that the model is well fitted. In deep learning, parameter tuning is the methodical process of modifying hyperparameters to improve the functionality of neural network models. Although deep learning models are quite adaptable, selecting the proper collection of hyperparameters is essential to maximizing their performance.By considering the above tuning parameter the evaluation result is as Table 5.1

5.5 Model Performance Comparison

All of the characteristics and elements in the data set are expected to be included in the model construction. When creating the model, the CDR data is modeled as time series data. The data set for the LSTM CNN-LSTM and CNN models is split into training and test data by the model created for this thesis. The model's parameters and specifications are recorded for the training and test data set using the first 80% of the CDR data starting on June 6, 2023. Before the final model is deployed, the model is validated using validation data since hyperparameters might affect the speed and accuracy of the final model. The performance of the various prediction models is compared using the latest 20% as test data.

The goal of model evaluation is to determine how well a model generalizes to test data that haven't been seen before. A constructed model's prediction performance is assessed using the three fundamental prediction metrics MSE RMSE, and MAE. The estimation of error determines the prediction's accuracy, therefore the more accurately the forecast, the lower the MAE, RMSE, and MSE values.

Table 5.1: Evaluation Result

Algorithm	MSE	MAE	RMSE
LSTM	0.0005668	0.01868	0.023808
CNN	0.000163443	0.010431	0.012784
CNN-LSTM	0.00056088	0.018598	0.023682

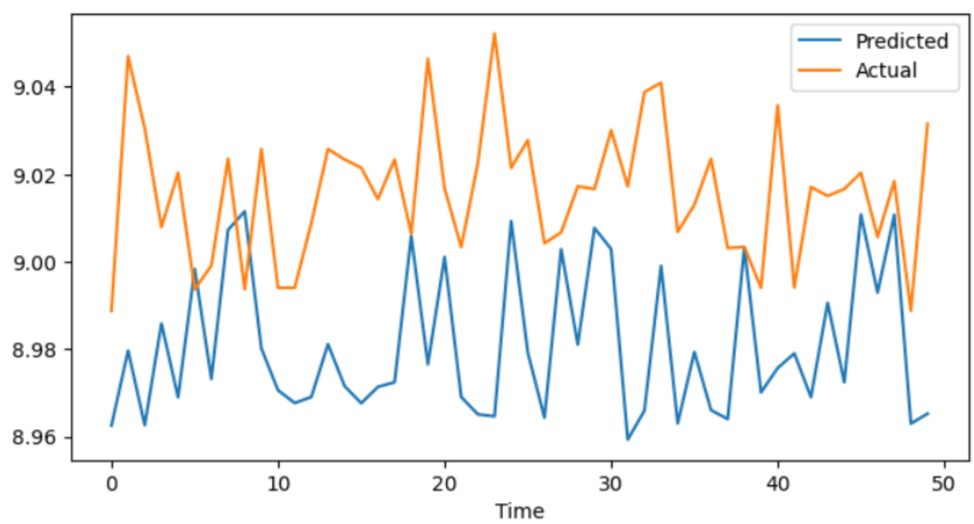

Figure 5.4: CNN-LSTM Predicted vs Actual

From Figure 5.4 the CNN-LSTM hybrid model's success in predicting a complicated place with a lower 0.00056088 MSE is attributed to its unique ability to combine LSTM's capacity to detect long-short dependencies with CNN's powers in extracting localized features. This combination enables the model to capture both immediate fluctuations and long-term trends in challenging and nonlinear time series data. Its versatility makes it a valuable tool for various applications where precise forecasting in complex environments is required.

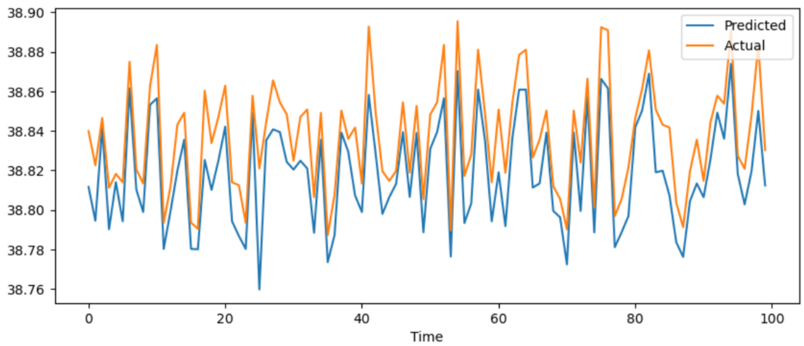

Figure 5.5: CNN Predicted vs actual

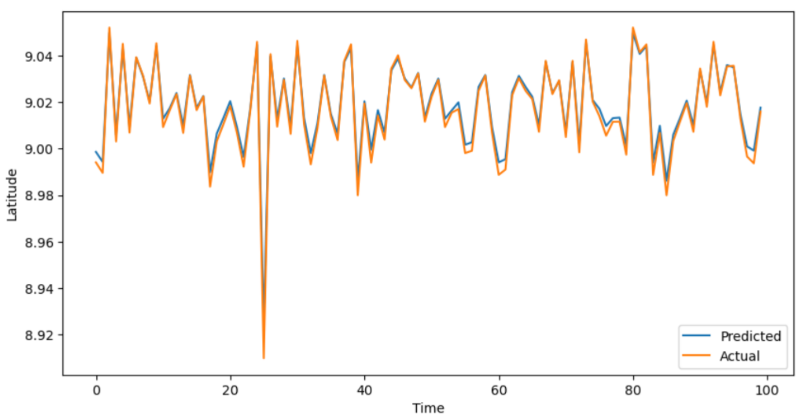

Figure 5.6: CNN Predicted vs actual value

from the Figure 5.5 and 5.6 the CNN's ability to achieve a remarkably low MSE of 0.0001634 when predicting a complicated place indicates its proficiency in handling complex, dynamic, and potentially nonlinear time series data. Convolutional more closest to the actual

actual dataset to capture local patterns from the past history. This makes it a valuable asset for a wide range of applications where precise forecasting is essential for informed decision-making and to users patterns. The LSTM model's strong performance in predicting the complicated place with a lower MSE highlights its ability to detect long-short dependencies in time series data and capture local patterns from past history. This makes it a valuable for various applications where understanding both short-term fluctuations and long-term trends is essential. Its adaptability to nonlinear and challenging data further solidifies its position as a reliable choice for time series forecasting in intricate scenarios. According to above figure the cuptared value by LSTM model is poor in location capturing than Convolutional LSTM and CNN.

By comparing the accuracy of the metrics and the performance of the deep learning models using deep learning hypermeter evaluation was successfully realized. In Table 5.1, a summary of the models' performance is provided. The most effective strategy is determined by comparing the outcomes of the experiment. Therefore, an experiment is carried out utilizing the chosen algorithms CNN, CNN-LSTM, and LSTM are respectively which able to forecast UE mobility patterns using previous stored in CDR dataset.

Chapter 6

Conclusion and Future work

6.1 Conclusion

Due to rising network demand and various user behaviors, the cellular network capacity is continually changing. As there are many real-world forecasting issues, predictive approaches become essential to capture the dynamics of mobile information demand. This study suggests a deep learning-based user mobility prediction model that makes use of multivariate input features to enhance the model's performance.

According to the above research, the deep learning algorithms CNN, LSTM, and CNN-LSTM are acceptable algorithms. To anticipate the next location based on historical information, the chosen models are trained with CDR data. The test data are used to evaluate the model. According to the findings, there is little difference between the deep learning models. The Ethiotelecom carriers can raise their quality of service by boosting user forecast accuracy.

The proposed CNN networks take advantage than both CNN-LSTM and LSTM ability to extract important features from the complicated and non-linear dataset. The model uses past data to forecast the sequential time series of CDR. The outcome suggests that a 1D CNN model can be an effective tool for CDR data analysis than Conv-LSTM and LSTM.

6.2 Recommendations for Future Work

Predicting multiple locations at once is possible as future study for this thesis. The accuracy of the prediction can be increased by accounting for holidays effects when predicting user mobility. The event or observation was captured in the time-series data. Any unique event (such as a festival or sporting event) has an impact on the outcomes of time series forecasting.

A possible future expansion may be to predict many places simultaneously, often known as multi-step location prediction. This is an advanced area of study in location-based forecasting. In this situation, the objective is to forecast a user's sequence of future places rather than just the next location.

Regarding multi-step location prediction and taking holiday effects into consideration in your thesis, keep in mind and expand on the following major points:

Multi-Step Location Prediction:

- For applications like route planning, individualized suggestions, and location-based services, multi-step prediction entails predicting a series of future locations.
- The difficulties and complexities of multi-step location prediction should be discussed, along with how the performance of the model is impacted by the prediction horizon (the number of upcoming steps).

Holiday Effects:

- Holiday and special event impacts on user movement patterns and, consequently, time series forecasting are referred to as vacation effects, sometimes known as holiday effects or seasonal effects.
- Time series models that include binary indicators for holidays and other special occasions can better express the influence of these occurrences.

With a special focus on multi-step location prediction, you can give a thorough review of its possibilities and difficulties by addressing these areas.

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APPENDIX A: MANUSCRIPT

Deep Learning Based User Mobility Prediction

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***Abstract*—Telecommunication service providers mainly emphasize on providing uninterrupted network access with the maximum attainable quality of service. With this in mind, service providers often monitor and utilize information acquired from user mobility patterns to performing effective resource management of network resources and to predict the user's future location. For instance, information associated with user mobility is used to reduces the cost of paging, managing the bandwidth resources and efficient planning. Overall, with the current trend of increase in the number of devices connected to mobile networks, telecom service providers are expected to carefully monitor and utilize user mobility patterns in order to improve the quality of service provided to their customers. With this understanding, in this thesis, we propose to utilize neural networks to predict user mobility, which helps to increase the performance of mobility analysis in cellular networks. This in turn is expected to improve the studying and under. In general, we intend to provide useful insights into how users migrate across various geographic areas and how they interact with the network infrastructure supplied by Ethiotelcom by constructing neural network based user predicting models. To meet this objective, we used mobility data obtained from Call Details Records (CDR) to forecast the future mobility of users (devices) as a sequential time series. Our experimental outcome suggests that a neural network based on one dimensional convolutional effective tool for user mobility analysis using datasets extracted from CDR. In reality, the Conv-LSTM networks take advantage of both an LSTM's ability to capture long-short dependency for time series data and the strength of the convolutional layers to extract localized features from complicated and non-linear dataset.**

Keywords: Telecom carriers, Mobility prediction, Resource Management, Deep Learning, cellular network.

I. Introduction

One of the crucial invention over the past decades is the emergence of mobile networks with the ability to make intelligent judgments to the demands of various service requests. This innovation has helped mobile network operators to provide a wide range of automated applications for prospective mobile end users in the area of internet of things. For instance, mobile users are able to conduct business, complete transactions, and enhance their mobile phone usage while they are in motion. Moreover, users may also conduct impromptu teleconferences, surf the internet, see high definition movies, listen to audio on the run, communicate to distant relatives, post images or videos to social media, etc. [1]–[3].

Practically, in addition to establishing user regulations, mobile network operators are expected to work hard to accommodate ever increasing demands by providing the resources necessary to ensure that mobile services are available to all interested users. In other words, the innovation that enhances the quality of life for every mobile user must address the increasing traffic needs which is expected to increase significantly within the next few years [4]–[6]. In reality, the increase in the demand of resources is highly correlated to advancements made in the application domain. For instance, the development of Internet of things (IoT), machine-to-machine (M2M) communications, the introduction of the fifth generation (5G) and beyond 5G (B5G). The wireless communication industry is now experiencing rapid growth in mobile communication. Mobility prediction is one of the key enablers that uses historical traffic information to predict future locations of traffic users. Accurate mobility prediction can help enable effective radio resource management, assist route planning, guide vehicle dispatching, or mitigate traffic congestion. Mobility prediction has been widely applied to mobile communication due to the increasing capacity requirements and requirements for quality of experience.

Overall, due to the mentioned and unmentioned reasons, data traffic generated by communication devices which is often linked to networks through Call Details Records (CDRs) has significantly increased. Consequently, telecom operators, such as Ethio-telecom, have now access to a vast quantity of data which could be utilized to raise the quality of service provided to their customers [7], [8]. In this regard, researches show that data flow from cellular networks,i.e., 2G/3G/4G/5G, is very helpful for studying human dynamics and providing trajectories of individuals on a big scale. For instance, by tracking people's movements' it is possible to gain the advantages of minimal energy usage, extensive coverage of a big population, and great cost effectiveness [9]. Moreover, mobility prediction is used in wireless networks to manage bandwidth resources and facilitate effective planning [10]. Overall, wireless networks use mobility prediction to execute

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efficient network resource management by forecasting a user's future position [11].

Even though predicting user mobility proved to be useful, selecting a proper predictive model is crucial in guaranteeing the usability (interpretability) of predicted outcomes. In this regard, deep learning-based (also called Deep Trip) algorithms have proved to be useful in forecasting a person's travel schedule in the future, even to possible departure times. For instance, [12], have shown that neural networks able to predict travel-related data, including destinations, departure times, and maybe additional specifics like mode of transportation, length of trip, and more. In reality, the forecasts ware made by observing previous travel data and sometimes additional relevant parameters. Generally, deep neural networks are a useful tool for machine learning and artificial intelligence in the field of wireless communication and network management because they may be used to predict the future locations of wireless network users. Overall, the use of deep neural networks to forecast the future locations of wireless network users is a potent tool for increasing services, managing the network better, and providing consumers with a seamless and effective wireless communication experience. With this said, we will present the statement of the problem we aim to address in this thesis.

II. Literature Review

In order to increase customer satisfaction and lower paging costs for telecom providers, the project tries to forecast user mobility using deep learning algorithms. Through a survey of the literature, the study looks at appropriate deep learning algorithms and then does an experiment to evaluate the selected methods. RNN, LSTM, and variations of LSTM are suitable deep learning algorithms for predicting user mobility, according to the results of the literature review. Utilizing accuracy criteria, the models are compared, and the experiment demonstrates that the individual model outperforms the global model in forecasting user movement. As a result, the research comes to the conclusion that the individual model is the best method for predicting user mobility [13].

According on an individual's movement patterns throughout time and their most recent visited areas, the paper referenced in the question attempts to anticipate where they will be in the future. The authors create a unique algorithm for predicting the next destination based on this mobility model, called n-MMC, by extending the Mobility Markov Chain (MMC) mobility model to include the n previously visited places. As soon as n = 2, the algorithm performs with an accuracy for the prediction of the next position in the range of 70% to 95%, according to the evaluation of the algorithm on three separate datasets. This research may have applications in the evaluation of geo-privacy methods, the creation of location-based services that anticipate a user's future move, and the planning of proactive resource migration that is location aware According on the previously visited places, the author of the article [14] uses a mobility Markov chain model to forecast the user's future location. The author proposed the n- Mixed Markov Model (n-MMC) algorithm, which keeps track of the user's prior location data over n places. To reduce location prediction issues, several researchers undertook numerous sorts of research and investigations.Using mobility, anticipate the next location Based on their mobility patterns throughout time, Markov chains are a method for predicting a person's next position. The mobility behavior of the person is modeled using Markov Chains, where the current location is used to anticipate the next one before moving to the next. Numerous applications, including location-based services, traffic forecasting, and urban planning, can benefit from this method. The n prior visited sites might be taken into account to increase forecast accuracy. The algorithm created for this method is cutting-edge and highly accurate at predicting a person's next location [14].

The mixed Markov-chain model (MMM) has a method for forecasting pedestrian movement called pedestrian-movement prediction based on MMM. The MMM considers the personality of a pedestrian as well as how the environment affects their mobility. With a prediction rate of 56.8%, this technique has been used to analyze pedestrian trajectory data. The movement of pedestrians in a certain location can be modeled using a Markov chain [15].

The task of "next location prediction" involves predicting a person's next location based on their past locations. Using deep learning models that take contextual features into account is one method for completing this objective. A deep learning-based model for predicting the future site was proposed by Xiaoliang F. et al., which models contextual variables among trajectories, such as periodic patterns and dynamic trajectory data, and mines similarity between potential destinations. For the purpose of predicting the next location, A. Sassi et al. suggested a model that makes use of deep convolutional neural networks with location embedding. Another recent method predicts the next location using transformer decoder-based neural networks based on previous locations and travel mode data. These deep learning algorithms use contextual data and massive location history datasets to increase the precision of next location prediction [16].

The authors of the study [17] developed a Time-series Forecasting- Recurrent Neural Networks (STF-RNN) model that uses a recurrent neural network to predict people's future whereabouts. The suggested recurrent model incorporates time and spatial interval sequences that are utilized to identify long-term relationships and assist the existing model perform more effectively. For forecasting people's subsequent movements using mobility data, the study's authors presented a novel model known as Space Time Features-based Recurrent Neural Network (STF-RNN). The STF-RNN model incorporates time and spatial interval sequences that are used to discover long-term relationships and help the current model function more efficiently in order to forecast people's future whereabouts1. The movement of individuals is controlled by both their current location and past moves, according to the model's underlying tenet. The STF-RNN model was created to forecast people's future locations based on their present position, past movements, and additional variables like the time of day, day of the week, and weather.The model may be used to forecast people's future movements with high accuracy because it was trained on a big collection of mobility data. Numerous applications, including traffic management, city planning, and location-based advertising, are possible for the STF-RNN model.

Due of the complex traffic network, predicting mobility via machine learning algorithms is a difficult task. However, a number of modern technologies have been introduced for predicting mobility. To determine the optimal approach for mobility prediction in mobile networks and the performance of each machine learning (ML) model based on the mobility model, mobile users' future locations are predicted. Extreme Gradient Boosting Trees (XGBoost), Semi-Markov, and Support Vector Machine (SVM) are four mobility predictors that were compared in order to determine which was the most effective. XGBoost was found to have a relatively high predictive accuracy and a short execution time [18].

Using a deep learning algorithm, mobility prediction in wireless networks focuses on forecasting the movements of various objects, including cars, animals, typhoons, and visitors in a wireless environment. The objective is to deliver an accurate and adaptive positioning system to enhance network resource management and forecast the future location of mobile nodes. The type of deep learning algorithms used for wireless network mobility prediction is extreme learning machines and deep neural networks. These algorithms are renowned for their capacity to model and forecast the mobility of any given node in a mobile ad hoc network, as well as their universal approximation [19].

An extensive analysis of deep learning solutions for different mobility tasks was provided by the results of a survey on deep learning for human mobility. The study of human mobility is important because it affects numerous areas of society, including the spread of disease, urban planning, well-being, pollution, and more. Deep learning has been used to human mobility as a result of the availability of digital mobility data, including call records, GPS location information, and social media posts, as well as the predictive power of artificial intelligence. A taxonomy of mobility tasks is provided, along with a discussion of the difficulties involved with each task and how deep learning might be able to get around some of the drawbacks of conventional models. The survey looks at the top deep learning solutions for crowd flow prediction, next location prediction, and trajectory generation [20]

III. Methodology

The many procedural processes for this research proposal will be completed. First, a review of the literature on the most recent developments in deep learning-supported user movement prediction will be done. The most effective historical techniques for making accurate predictions will then be looked at. We will outline a novel approach for better user mobility prediction based on the state of the art. The new strategy will then be put to the test in an experiment, with the results being examined. Lastly, contrast the novel outcome with more traditional state-of-the-art techniques.

In Figure 1, the suggested design of the system is illustrated, starting with dataset collection. A dataset is chosen for training and testing. The data preparation will be the end of

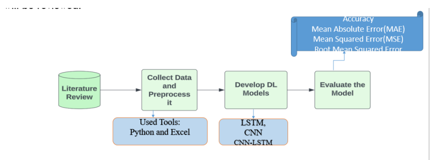


Fig. 1. Research Methodology

data processing which can lead the data to be used by a deep learning model. Then the next step is the training of model to utilizing each of the datasets. The system is currently prepared for testing and performance analysis.

A. System Model

To get the required model fit, the hyperparameters can be modified by examining these scenarios. The process of parameter tuning is essential to the creation of deep learning models. To make sure a model works well with unknown data, hyperparameters must be chosen, optimized, and evaluated. The right parameter adjustment can result in models that generalize well and provide reliable predictions.

Throughout parameter adjustment the Model evaluation is essential to monitor how well the model matches the training set of data. If the model is underfitting, it is too simple to detect the fundamental trends in the data. Because the model is extremely complex when it is overfitting, it fits noise in the data rather than the actual patterns. If a model is good fit, the training and validation data fit the model well in terms of generalization.

The data collection is modeled as a time series of sequential data, and it is believed that the model construction would capture all of its properties and elements. The model is created for an LSTM, CNN and CNN-LSTM algorithms are employed.

The most hyperparameters considered in our models are learning rate, Number of Layers and Units, activation functions, dropout, batch-size and epoch.
The model is trained with those optimal parameters in methodology section using a training dataset, and the performance of the model is evaluated with a validation dataset. The algorithm analysis is done in above Figure 2 block diagram steps.

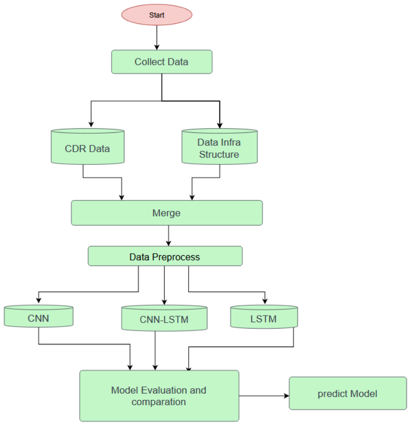


Fig. 2. System Model

Parameter tuning is performed for some hyper parameters to obtain a better result. The model was checked whether it is overfitting, under fitting, or a good fit before the final evaluation of the model with the test set.

B. Data preprocessing

- The primary data sources CDR data and dataset Parameters are collected from two different department
- Data cleaning:-handling missing value and removing unwanted data
- To capture a representative snapshot of user behavior, network activity, and potential variations over time of june 6, 2023 to 12, 2023
- Multivariate features from the CDR dataset include timestamps, user identities, cell IDs, and the dataset parameter
- CDR data and Dataset parameter have a lot of features, but only a few parameter we have used and displayed in the Table below

TABLE I
SELECTED CDR DATASET

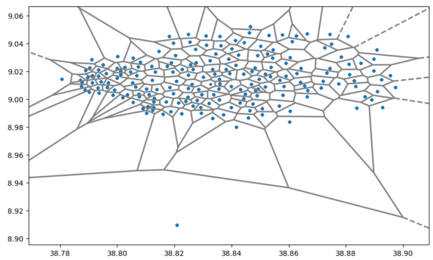
Timestamp	Cell Id	User Identity
2023-06-05 22:58:24	1	102
2023-06-05 23:20:09	2	70
2023-06-05 23:59:34	3	80

TABLE II
SELECTED DATASET PARAMETER

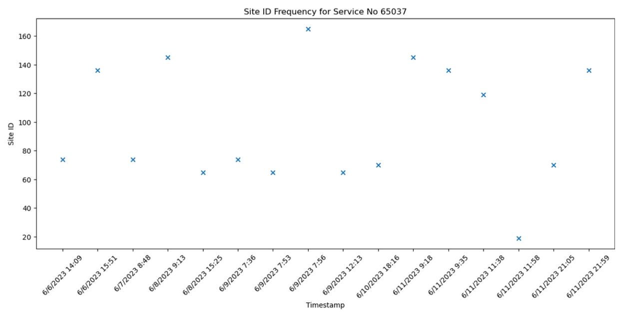
Cell Id	Latitude	Longitude	Site ID
1	9.1392	38.7873	113300
2	9.1392	38.78733	113300
3	9.1392	38.78733	113300

- Merging Data: The data is merged based on Cell ID to ensures dataset is structured around cellular network locations informations
- Data labelling:-my data is in large digits and will need to be labeled

- Setting Data Sequencially and Split data:-
  - Training dataset: 80% dataset will be used for training which is 111996 used for training purpose
  - Test dataset: 20% dataset will be used for test the model which is 28000 are sampled for testing purpose.
  - Selected location and site distribution is represented as Cells Visualization below



  - After Training the patterns of our data to visual user mobility of User Identity is shown below



  - Shows a user mobility scenario, by representing Y-axis site Id and X-axis timestamp of user Service No

The model is properly constructed for the unique properties of the time-series data, which is important for making precise predictions. After the model was constructed, it was tested against a validation data set to see if it was over fitting, under fitting, or a good fit. Over fitting: When a model performs well on training data but poorly on test data Good fit the training and validation data fit the model well in terms of generalization Under fitting: When a model to have high training data and high test error performance evaluation metrics for regression model.

Mean Squared Error (MSE):average squared deviation between the expected and actual values.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \tag{1}$$

where N is the number of data points, and y_i and $(\hat{y}_i)$ are the actual and predicted values, respectively.

Mean Absolute Error (MAE): the difference between the actual and predicted amounts in absolute terms.

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i| \quad (2)$$

Root Mean Squared Error (RMSE)

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (3)$$

C. Model Configuration

- To address the regression issue for time series problems the suggested models for this study are: CNN, LSTM and CNN-LSTM model

TABLE III
HYPERPARAMETERS USED IN CNN MODEL

Hyperparameters	Values
Filter size	16 and 8
Kernel size	1
Batch size	16
Loss	MSE
Optimizer	Adam
Activation	(ReLU) and Linear
Epoch	10

- Hyperparameter (optimizer type, loss function, activation function, Learning Rate, Epoch, Batch-Size and Dropout) should be initialized

TABLE IV
HYPERPARAMETERS USED IN LSTM MODEL

Hyperparameters	Values
Hidden layer Neurons	Layer1 16 layer2 8
Batch size	64
Dropout	0.7
Optimizer	Adam
Activation	(ReLU) and Sigmoid
Epoch	10

- Hyperparameter (optimizer type, loss function, activation function, Learning Rate, Epoch, Batch-Size and Dropout) should be initialized

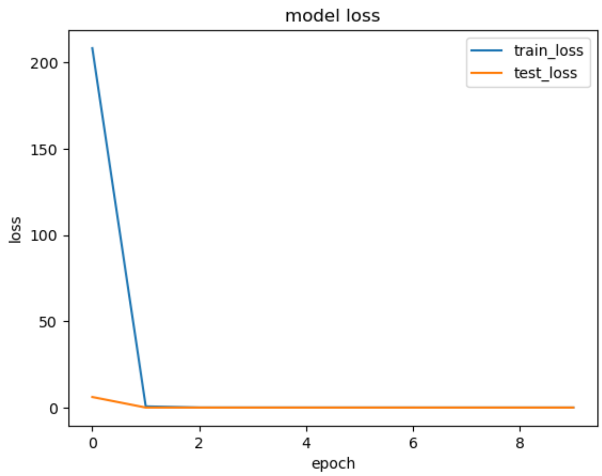
TABLE V
HYPERPARAMETERS USED IN CNN-LSTM MODEL

Hyperparameters	Values
Hidden layer Neurons	Layer1 16 layer2 4
Batch size	16
Dropout	0.5
Optimizer	Adam
Activation	(ReLU) and Linear
Epoch	10

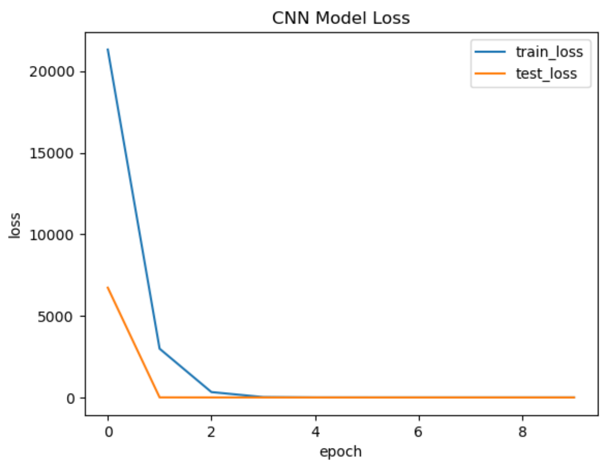
D. Result and Discussion

LSTM LOSS

- When we formulate the model, the CDR data is modeled as time series data
- by adjusting the above parameters it give 0.0005668 of MSE that is close to zero and it increases accuracy of models to predict
- The evaluation of training and validation error against about 10 epochs,
- the MSE becomes more approach to zero and the same for both training and validation datasets
- The model is well fitted and ready to evaluate with the test dataset, specifically when epoch is above 1



- The MSE becomes more approach to zero and the same for both training and validation datasets.
- The model is well fitted and ready to evaluate with the test dataset, specifically when epoch is above 3



- The same to LSTM the evaluation of training and validation error against about 10 epochs,
- The MSE value is very low for both training and validation datasets

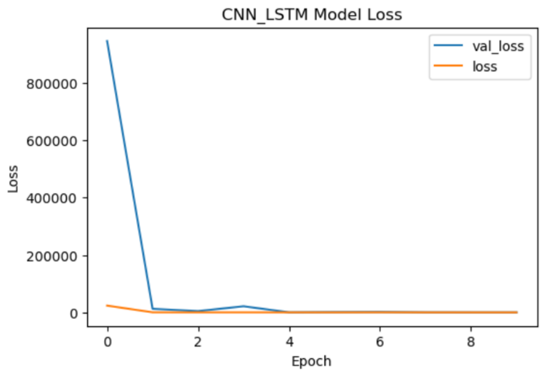
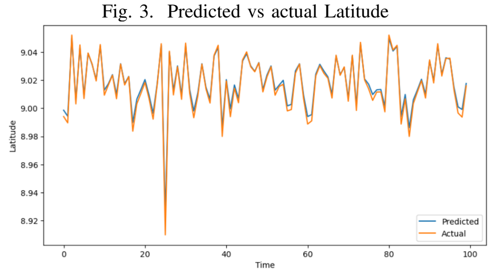
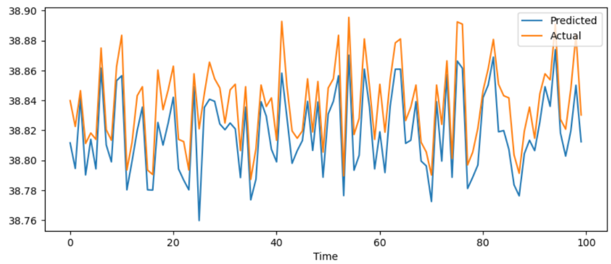


Fig. 3. Predicted vs actual Latitude



Predicted vs Actual latitude
Predicted vs Actual longitude



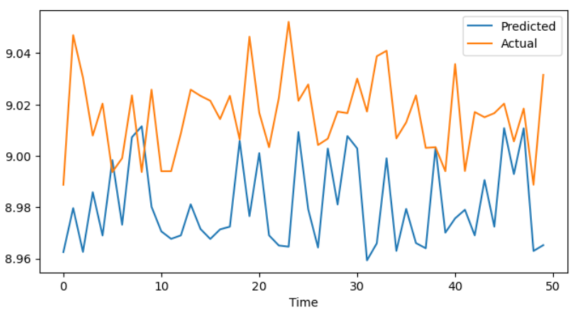
- The lower the value of mse increase the accuracy of the model
- A constructed model's prediction performance is assessed using the three fundamental prediction metrics MSE RMSE, and MAE
- The estimation of error determines the prediction's accuracy, therefore the more accurately the forecast, the lower the MAE, RMSE, and MSE values

TABLE VI
EVALUATION RESULT

Algorithm	MSE	MAE	RMSE
LSTM	0.0005668	0.01868	0.023808
CNN	0.000163443	0.010431	0.012784
CNN-LSTM	0.00056088	0.018598	0.023682

- The CNN-LSTM hybrid model's success in predicting a complicated place with a lower 0.00056088 MSE is attributed to its unique ability to combine LSTM's capacity to detect long-short dependencies with CNN's powers in extracting localized features

Predicted vs Actual latitude



- The CNN's ability to achieve a remarkably low MSE of 0.0001634 when predicting a complicated place indicates its proficiency in handling complex, dynamic, and potentially nonlinear time series data.
- Convolutional more closest to the actual actual dataset to capture local patterns from the past history

- LSTM model's strong performance in predicting the complicated place with a lower MSE highlights its ability to detect long-short dependencies in time series data and capture local patterns from past history

The LSTM model's strong performance in predicting the complicated place with a lower MSE highlights its ability to detect long-short dependencies in time series data and capture local patterns from past history. This makes it a valuable for various applications where understanding both short-term fluctuations and long-term trends is essential. Its adaptability to nonlinear and challenging data further solidifies its position as a reliable choice for time series forecasting in intricate scenarios. According to above figure the cuptared value by LSTM model is poor in location capturing than Convolutional LSTM and CNN.

By comparing the accuracy of the metrics and the performance of the deep learning models using deep learning hypermeter evaluation was successfully realized. In Table VI, a summary of the models' performance is provided. The most effective strategy is determined by comparing the outcomes of the experiment. Therefore, an experiment is carried out utilizing the chosen algorithms CNN, CNN-LSTM, and LSTM are respectively which able to forecast UE mobility patterns using previous stored in CDR dataset.

CONCLUSION

Due to rising network demand and various user behaviors, the cellular network capacity is continually changing. As there are many real-world forecasting issues, predictive approaches become essential to capture the dynamics of mobile information demand. This study suggests a deep learning-based user mobility prediction model that makes use of multivariate input features to enhance the model's performance.

According to the above research, the deep learning algorithms CNN, LSTM, and CNN-LSTM are acceptable algorithms. To anticipate the next location based on historical information, the chosen models are trained with CDR data. The test data are used to evaluate the model. According to the findings, there is little difference between the deep learning models. The Ethiotelecom carriers can raise their quality of service by boosting user forecast accuracy.

The proposed CNN networks take advantage than both CNN-LSTM and LSTM ability to extract important features from the complicated and non-linear dataset. The model uses past data to forecast the sequential time series of CDR. The outcome suggests that a 1D CNN model can be an effective tool for CDR data analysis than Conv-LSTM and LSTM.

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