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Predicting IoT-based Traffic in Smart Cities using Neural Networks

By

YangHua Wang

Advisor

prof. Ing. Petr Hajek, Ph.D.

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prof. Ing. Jan Stejskal, Ph.D. m.p.
Dean

RNDr. Ing. Oldřich Horák, Ph.D. m.p.

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ABSTRACT

Congested road networks are negatively impacting the sustainability of many cities due to worsening air contamination. Smart blocking management permits road users to avoid blocking areas and reduce pollutant concentrations. However, according to the nonlinear moving behavior of traffic flow, it is difficult to accurately predict the degree of congestion. With the proliferation of IoT devices and the fast development of machine learning and the emergence of new data sources, the inspection and prediction of traffic situation in smart cities are more accurate than ever before. This helps to optimize the structure and management of transportation services in smart cities. In this study, neural networks with deep learning are used to predict traffic in smart cities. I use a data set called traffic, which was collected by sensors placed at four intersections, and then the time series forecasts are produced based on the GRU model, which is thoroughly investigated using different settings.

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ANOTACE
Tato práce se zaměřuje na predikci provozu na bázi internetových věcí v chytrém městě pomocí neuronových sítí. Účelem je využít velká data shromážděná zařízeními IoT, jako jsou senzory a kamery, k vývoji přesných modelů predikce provozu. Cílem studie je porozumět modelu GRU založenému na architektuře rekurentních neuronových sítí (RNN) pro zachycení časových a prostorových závislostí v provozních datech.

KLÍČOVÁ SLOVA
chytrá doprava, chytré město, internetová věc, strojové učení, neuronové sítě

TITLE
Predicting IoT-based Traffic in Smart Cities using Neural Networks

ANNOTATION
This thesis focuses on predicting IoT-based traffic in smart cities using neural networks.The purpose is to use the big data collected by IoT devices, such as sensors and cameras, to develop accurate traffic prediction models. The study is to understand GRU model based on recurrent neural networks (RNNs) architectures to capture temporal and spatial dependencies in the traffic data.

KEYWORDS
smart transportation, smart city, internet of things, machine learning, neural networks

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List of Abbreviations

AI	Artificial Intelligence
CNN	Convolutional Neural Network
GPS	Global Positioning System
GRU	Gated Recurrent Unit
ICT	Information and Communication Technology
IoT	Internet of Things
LSTM	Long Short-Term Memory
MAE	Mean Absolute Error
NFC	Near-Field Communication
R^2	Coefficient of determination
RMSE	Root Mean Square Error
RNN	Recurrent Neural Network

1 Introduction

Predicting is something people are continuously attempting to do, and individuals too utilize innovation for traffic management. In the event that they know the changing of the entire street, the department of traffic can superior control the street amid top hours, do a great work on activity administration, and apportion assets. For ordinary people, the traffic congestion information obtained through the application can make traffic planning, avoid busy roads, and save time, so traffic forecasting is of great importance to everyone.

Now, with the process of urbanization and the growth of the world's population, the universalization of cars, and the application of smart cities to urban services are becoming more and more extensive. Smart city services can reflect the needs of industry and commerce, daily life, public safety, and real-time traffic conditions. With the development of smart cities, our urban ecosystem can provide us with more data.

The good news is that propels in Internet of Things (IoT)-based applications, data communication innovations, machine learning, information mining, design acknowledgment procedures, and information integration are the key components that driven to the development of unused advances that are the most reasons for the appearance of smart cities.

"*The urban mobility in smart cities highlights several issues that are anchored on sustainable development, which aims to make them more attractive, more ecological, and more economical while strengthening the social link*." (Koumetio Tekouabou et al., 2022, p. 688).

In this vigorous wave of artificial intelligence, we found that, for commercial enterprises, artificial intelligence does not bring them much so-called intelligence, but what it does bring is a key component of intelligence: AI prediction. Data generated from various sensors is streamed onto the network and used as the data source for these classification and regression models to predict outcomes (Diwakar Babu, 2019).

The IoT implies the reliably created framework of physical things that highlight an IP address for the Web organization and the correspondence that happens between these objects and other Internet-enabled gadgets and systems (Jabamony & Shanmugavel, 2019).

The smart transportation system course of action due to the Net of Things utilizes advanced data collection techniques, comprehensive data-taking care of methodologies, and a marvelous arrangement for planning information, combined with a beneficial commerce appearance, which can effectively progress the enthusiastic advancement of the brilliant transportation system industry.

To make strides, the existing activity administration framework basically centers on manual mediation and administration, primarily on crossing point flag control, with few street surface data collection focuses, partition of vehicle and street administration, and autonomous operation of the framework, which is shown as flawed, uncertain, and less than ideal.

This work aims to characterize intelligent traffic management, introduce neural networks for time-series forecasting, propose an IoT-based traffic forecasting system based on neural networks, preprocess traffic time-series datasets, validate proposed forecasting systems using datasets, and discuss the results.

2 Literature Review

2.1 Definition of IoT-based Traffic

With the research and rapid maturity achieved through the IoT over the past few years, urban transportation is also developing in the direction of intelligence. The IoT has improved the level of informatization and automation of intelligent transportation, and the value of transportation infrastructure has also increased, making the connection between vehicles, people, and transportation infrastructure stronger.

The IoT continues to improve at the physical level, based on IP addresses, enabling it to communicate with other Internet devices and systems. In essence, the IoT is an information system in which each entity exchanges information with the Internet through Internet devices or switches (Jabamony & Shanmugavel, 2019).

The IoT is also a technical term developed by information technology. As the most important part of Internet technology and development in the world today, the IoT uses video image recognition, intelligent positioning systems, and other information- sensing equipment to connect any object to the Internet according to customized requirements. Exchange and communication based on intelligence have evolved into a smart network with identification, positioning, monitoring, and management capabilities and characteristics.

The IoT sets up contact between objects and people and between people and objects so that they can be related and associated with each other. The traffic management platform built with IoT technology is a transfer station and collection center for all information and uses artificial intelligence and big data as the basis for reasonably processing and guiding vehicles and pedestrians through reasonable, scientific, and logical traffic decisions.

If traffic is based on the technology of the IoT, then a non-static, unmanned, intelligent, traffic management model can be realized in life. Dynamic traffic nodes can collect real-time traffic conditions, traffic signals, and congestion status on roads or intersections through automated and intelligent systems. This technology can dynamically manage traffic.

Because of the effect of globalization, the cost of sensors can be reduced, so that we can deploy them in economic life on a large scale, and the model of the main platform and the secondary platform can be established, so that we can operate the sensors deployed in different life scenarios under the same system, so as avoid confusion and repeated deployment, and we can grasp the overall situation in real time. Superimposed layout of different types of heterogeneous hubs can be automized to achieve data collection strategies of different quality, combined with collaborative preparation and design confirmation, to ensure the accuracy and automation of excellent traffic system judgment and decision-making, reduce workload and manual intervention, and save resources input.

The smart transportation framework based on the IoT innovation has the essential shrewd characteristics of detectable quality, judgment, controllability, reasonability, programming, energy, and worldwide reach.

In short, the essence of the IoT transportation is an open and comprehensive interpretable network that can automatically organize, resources and data, and information sharing. It can respond to the changes in real life in real-time according to the environmental change in real life. (Madakam et al., 2015). But besides, there are various inadequacies inside the current IoT, such as:

- Maturity - The future will be the era of the Industrial IoT. However, there are still maturity problems in the Industrial Internet.
- Digitalization - It is not simply putting an "intelligent solution" into your device, and then you can get all positive results, insights, and actions. Within the early stages, an expansive sum of venture and a huge sum of information collection and analysis have driven to the primary of numerous early trials. This is a very common reason for the recent failure of IoT projects.
- Lack of skills - The IoT requires a lot of experience on designing and engineering involvement, and most companies or people don't have it.
- Software vulnerability - There are a large number of low-quality software with a large number of vulnerabilities installed on IoT-based devices, which are very vulnerable to various attacks and the risk of information leakage. Gadgets are defenseless to computer program assaults, powerless encryption, confirmation disappointments, and program-sending challenges, among other variables. Furthermore, the vulnerabilities of IoT gadgets can effortlessly lead to assaults that uncover the arrange on which they dwell. Typically genuine for both homes and businesses, as IoT gadgets that come up short to secure the remote network's certificates can uncover the whole arrange. Within the current climate, where numerous individuals are working remotely, a single IoT disappointment can lead to assaults influencing domestic and trade systems.

- Features of innovation: Innovative features driven by complexity, compatibility, and security concerns related to innovation and design (Olushola, 2019).
- Complexity - The Web of Things is much more complex than already assessed. To begin with, there are numerous choices for IoT networks, but this difference is negative instead of valuable. IoT pioneers ought to either select a single network arrangement, constraining their choice of distinctive gadgets and innovations, or go to the inconvenience of building numerous network arrangements. The Web of Things too requires well-equipped and wealthy equipment, software, and information capacity frameworks, so information technology frameworks ordinarily get changed and overhauled sometime recently, but the specified adequate venture is not within the reach of each company.
- Interoperability - In the consumer market, there are a lot of embedded smart devices, but few standards or interoperability specifications for smart homes or smart buildings. At the same time, multi-vendor solutions can make IoT applications more robust. However, without a high enough security standard so that we can exchange data with confidence, the IoT cannot fully exert its capabilities.
- Need of security - Nothing is wrong here, the IoT has indeed brought a really great time to our lives, but security issues can never be dodged, and they will continuously be closely related to the Web of Things. Since, to realize the anticipated objective, the information trade of IoT-based gadgets must to begin with be carried out on the Web, and there are numerous arrange aggressors, it is amazingly simple to cause data leakage.

Therefore, devices based on the IoT must encrypt information using the most advanced technology and then share it to effectively prevent data leakage. In the event that the encryption is too complex, it regularly raises concerns about the unwavering quality of the gadget or framework. Since the IoT could be an exceptionally complex and huge network with numerous branches, equipment failure is additionally possible.

2.2 Definition of Smart City

The development and growth of IoT technology have opened up new chances, one of the most striking applications of which is related to the evolving paradigm of smart cities. Generally speaking, it can be defined as the incorporation of the IoT and Information Communication Technology (ICT) into urban management, aiming to cope with the exponential growth of urbanization and population, thereby significantly improving people's quality of life (Belli et al., 2020).

Smart city has three essences and four characteristics, and its three implications are as follows (Joshi et al., 2016):

(1) A smart city may be an organized, data, and intelligent city with exceedingly coordinated data innovation and profoundly coordinates data applications.

(2) Smart city is the embodiment of the current social information technology level, continuous progress, and continuous development, which has reached a very high stage, with stronger capabilities of independent learning, self-correction, self-improvement, and innovative development.

(3) Smart city could be an unused demonstration of urban advancement with shrewd innovation, keen industry, shrewd humanity, keen benefit, shrewd administration, and smart life as its vital substance.

The four characteristics of smart cities are summarized as follows (Joshi et al., 2016):

(1) Comprehensive sensing: Sensors sent on an expansive scale in daily life and put frame the Web of Things to degree, screen, and analyze the center frameworks of city operations.

(2) Full integration: The Web of Things and the Web framework are completely associated and coordinated and the information is coordinated into a full picture of the operation of the city's center framework to supply a shrewd foundation.

(3) Incentives for innovation: Energize governments, ventures, and people to carry out imaginative applications of innovation and commerce based on the keen framework, and give a relentless stream of advancement energy for cities.

(4) Collaborative operation: Based on a savvy foundation, different key frameworks and members within the city cooperate harmoniously and efficiently to realize the most excellent state of urban operation.

Finally, the comprehensive definition of smart city can be given as follows: "*a smart city is a well-defined geographical area, in which high technologies such as ICT, logistics, energy production, and so on, cooperate to create benefits for citizens in terms of well-being, inclusion and participation, environmental quality, intelligent development; it is governed by a well-defined pool of subjects, able to state the rules and policy for the city government and development*" (Dameri, 2013, p. 2459).

2.3 Smart Transportation

Smart transportation is the comprehensive application of progressed science and innovation, such as data innovation, computer innovation, information communication innovation, sensor innovation, etc., to transportation, benefit control, and vehicle fabrication to fortify the relationship between vehicles, streets, and clients. In arrange to create a comprehensive transportation framework that ensures security, moves forward productivity, progresses the environment, and spares vitality, it is additionally a critical pointer for the development of a smart city.

As a large-scale and all-round transportation and administration framework, much appreciated for the fast advancement of the IoT in a long time, it combines progressed control, detection, communication, data technology, and computer innovation productively and comprehensively applies to the whole activity administration framework. Since it has enormously reduced activity blockage, viably diminished the event of activity mishaps, improved the security of the traffic framework, and decreased natural contamination, it has ended up the foremost role within the field of the IoT.

The foremost vital point of smart transportation is to transport travelers from point A to point B in a quick, secure, and energy-saving manner. In arrange to attain this objective, the development that has to be done is as follows (Azgomi & Jamshidi, 2018):

- Data collection: Use hardware equipment to collect information 24 hours a day.
- Data transmission: The data obtained through IoT devices in real-time needs to be transmitted immediately to the rear data processing center.
- Data analysis: Analyze the data after receiving it, extract the information we need, and at the same time use SMS or applications to feed back the results to passengers.
- Traveler data: Give travelers with an exact evaluated time of entry at their goal, and give a precise evaluated time of entry for travelers holding up to reach it.

- The use of near-field communication (NFC): The broad utilize of NFC in a expansive range will too move forward the comfort of smart transportation to a certain degree.
- Driver investigation framework: The savvy gadgets coordinates into the vehicle can be utilized to gather and analyze the real-time circumstance of the driver and can make successful reactions for the security of travelers and macro-traffic control.

To form an economical transportation framework, it is beneficial to use and apply cutting-edge communications, gadgets, and computing capabilities empower data exchange, activity stream control, and transportation arrange administration (Oladimeji et al., 2023).

The following cases are presented to illustrate the best practice of smart transportation:

Vienna, Austria

Vienna has 5 underground lines, 28 cable car lines, and 128 transport lines. Vienna's metro framework transports 1.3 million travelers a day, making it the best-performing open transport framework in the world, agreeing to the Worldwide Affiliation of Open Transport. All of these administrations can be effectively explored through a smartphone app, overhauling travelers when another cable car, metro, or transport clears out (Hamza, 2021). In Vienna, savvy innovation is additionally being utilized to make strides in open transport for citizens with extraordinary necessities. In expansion to a multi-sensory route framework, and station service information counting notice of current lift disappointments, there's a custom course organizer for the hearing and outwardly disabled.

Barcelona, Spain

In expansion to proficient open transport, Barcelona moreover features a organize of savvy activity lights that, among other things, give "green light" courses for crisis administrations. This allows vehicles such as ambulances and fire trucks to supply crisis help more rapidly (Hamza, 2021). A few plans have been actualized in Barcelona, counting intelligently touch-screen data shown at transport stops, keen stopping sensors that permit drivers to check where there are free spaces (lessening time went through looking for a stopping space on the road), bike-sharing system Bicing and shared electric bikes lease. All of this combines to form Barcelona into a keen and habitable city and a perfect area for Versatile World Congress (Hamza, 2021).

Tokyo, Japan

The Yamanote Line, a circular line around central Tokyo, is the biggest transport framework in the world, utilized by 34 million travelers each week. Keeping up the line is challenging since trains run each two to three minutes from early morning until late at night. IoT innovation empowers administrators to move from a wasteful planned support framework to a savvy upkeep framework (Hamza, 2021). "Condition Maintenance" utilizes IoT innovation to gather and analyze gear condition information. It makes a difference to recognize shortcomings, anticipate failures, and plan repairs. Tokyo is utilizing IoT to form secure, dependable railroads and diminish the requirement for support shutdowns.

London, England

London has the most seasoned underground framework in the world. It is moreover one of the biggest and most crowded cities in Europe, and travel, particularly amid surge hours, can be moderate and upsetting. Numerous tram lines are running at the most extreme capacity. With the taking toll of building unused underground framework restrictive, London specialists are taking more imaginative approaches to the issue. In addition to getting more people to ride bicycles, it will also make the public transportation system smarter. After numerous a long time of attempting to organize the complex support needs of such a large and sprawling Underground framework working on closed-circuit television camera frameworks, lifts, open address frameworks Web-enabled sensor speakers, air-conditioning frameworks, and metro burrows were introduced. Their central control center employments amassed sensor information from these sensors to track hardware issues and send support groups. This spares cash and diminishes repair-related delays.

San Francisco, United States

One of their keen city ventures is SFpark, which employments remote sensors to identify the inhabitance of stopping spaces in metered spaces. The city can at that point utilize this data to alter stopping costs. Estimating stopping at a cost to guarantee certain geographic ranges will be accessible and altering rates so they are never so moo that the space is continuously involved, or so tall that there is a part of vacancies. San Francisco has sworn to decrease single-person vehicle trips by 10 % by exchanging open travel, shared, and dynamic transportation. Making strides in open transport frameworks utilizing associated advances will be key in case they need to realize this objective. Joining forces with a few of the world's biggest tech companies on the doorstep ought to be doable (Hamza, 2021).

2.4 Limitations of Current Traffic Management

In afterward a long time, with the speedy monetary and social change, the scale of the city has kept on grow, the method of urbanization has kept on quicken, the urban population has developed quickly, the request for transportation has expanded significantly, and the initial balance of transportation supply and request has been broken. On the contrary, the urban infrastructure and the methods of the traffic management department are outdated and the personnel is insufficient. They are no longer able to cope with the traffic needs of the current high-speed development, still in a period of exploration, experience, and growth (Dai, Ma & Xu, 2019).

The existing activity administration framework is primarily based on manual mediation and administration, primarily on crossing point flag control, with few street surface data collection focuses, isolated vehicle, and street administration, and autonomous operation of the framework, which is inadequate, uncertain, and inopportune. Its main flaws are (Ni, 2020):

- Non-dynamic - Too expensive sensors limit the popularization and scale of intelligent transportation, and a little sum of street surface data collection is concentrated on the hubs of the street arrange basically at crossing points. This limitation makes it incomprehensible to gather traffic comprehensively and viably all sorts of data within the framework cannot powerfully and precisely reflect the precise state of the activity framework.
- Non-global - The existing cleverly transportation framework extend arranging and development are autonomous of each other, the data collected by each framework cannot communicate with each other, and the interfacing between frameworks or hardware of diverse gear producers are not open, coming about within the examination and judgment of activity conditions. The potential coordination impact of activity data may cause rehashed development of frameworks or capacities, rehashed collection of information data, and the judgment coming about of autonomous frameworks that are not comprehensive and general.
- Non-automated - At show, cleverly transportation based on the Web of Things has exceptionally few strategies for collecting data, and it cannot ensure the exactness of activity choices. The operation and decision-making of the activity framework frequently require a parcel of labor, support, mediation, judgment, and insights.

3 Methodology

This chapter depicts an approach to anticipating IoT-based traffic in smart cities utilizing neural networks. This approach includes data acquisition and preprocessing techniques, neural network model development, and performance evaluation.

3.1 Data Collection

Traffic information automatic collection methods mainly include manual counting method, test vehicle moving survey method, photography method, vehicle detector measurement method, GPS floating car method, mobile phone positioning method, remote sensing image processing, and so on. Non-automatic collection technology does not have the function of automatic collection, and the collection process relies on manual operation. It is generally suitable for short-term traffic surveys, but not for real-time traffic information collection.

IoT gadgets prepared with different sensors, such as cameras, activity stream sensors, and GPS trackers, are deliberately conveyed over the city to capture activity data. in genuine time. These sensors are found at major convergences, thruways, and major streets to guarantee comprehensive scope.

The deployed IoT devices continuously capture traffic-related data, such as the number of vehicles, speed, number of clients, and travel time, at standard interims. Collected information is transmitted wirelessly to a central information store to encourage handling and investigation.

In expansion to information from IoT sensors, pertinent outside information sources, such as climate conditions, occasions, and street development plans, are coordinated into the information set. This extra data makes a difference capture outside variables that can influence activity designs and makes strides in the model's forecast accuracy.

This study will investigate four intersections and will use the existing traffic flow dataset named Traffic[1] (Moriya, 2021), including four attributes "date", "intersection" (Junction 1,

[1] https://www.kaggle.com/code/bhavinmoriya/trafficpredictiongru/input?select=traffic.csv

Junction 2, Junction 3, Junction 4), "vehicle information", "ID", so the flow data contains three main types of features: temporal features, spatial features, and periodic features (Arem, 2006).

3.2 Data Preprocessing

First of all, we need to check whether the received data are lost or violate the rules. If there is missing information, then we need to use appropriate strategies to fill it in and handle it appropriately according to the degree of loss. Or use strategies like information smoothing or outlier exclusion to identify and handle anomalies.

Next, missing values need to be dealt with. In real data, missing values are very common. This could be due to human error, system error or data collection issues, and so on. There are several ways to deal with missing values in machine learning, such as removing rows or columns containing missing values (Qiu, 2016). Filling includes filling missing values with mean, median, mode, interpolation, and so on.

Then, the data needs to be transformed and normalized. In machine learning, diverse calculations may have diverse necessities for the frame of the information. Hence, the information ought to be changed and normalized so that the calculation can work superior. These transformations may include normalizing or standardizing the data, feature scaling or discretizing the data, and so on.

Also, outliers need to be dealt with. An exception ordinarily alludes to an information point that is altogether distinctive from other information focuses. In a few cases, exceptions may be rectify, and in other cases, they may be off-base. Therefore, outlier detection and processing of the data is required.

Finally, data quality needs to be ensured. Data quality is a very critical issue. Even the best machine learning algorithms can get inaccurate results if the data quality is poor. To ensure data quality, data needs to be checked one by one, and measures are taken to eliminate or reduce errors.

The data set we used has already been processed. In the CSV format, it is divided into four parts: Datetime, Junction, Vehicles, and ID. But we still did some processing according to my own needs. I imported the Date Time library in Python and converted Date Time into five parts: Year, Month, Day, Hour, and Date_no (see the code in the Appendix).

I imported the dataset Traffic that I need to use in the code stage, and imported the dataset using the Pandas library through Python, and then we can read the four attributes as DateTime, Junction, Vehicles, ID, where the ID feature was dropped off.

After that, we need to split the obtained DateTime attribute into four features Year, Month, Day, and Hour. We can use these four features to see the trend of traffic flow changes in different time units. After that, we need to sequentially divide the data set into training set and test set. The method I just used 90% for the training set and 10% for the test set. In this way, we have processed it and obtained the data we use for neural networks.

3.3 Neural Network Model

Developing neural network models is an important step in predicting IoT-based traffic in smart cities. This section describes the steps required to develop a model.

Different forecasting tools are supported by various models or algorithms. We need to determine which predictive model or tool is more suitable for our research goals, use the predicted results for analysis, and combine data to make informed decisions (Kashyap, 2022).

Time-series models are formed by obtaining a sequence of data points, which are entered into the program as time parameters. Generally, the past data is used as a data set for training, and the obtained parameters are used to predict the data in the next few weeks (Lim & Zohren, 2021).

If the manager of a restaurant wants to predict the number of customer visits, he may use traditional methods to make statistics and then calculate the average. But development is not inactive, it is unstable. Therefore, it is necessary to use the time-series model to achieve the forecast effect and keep the company's growth trend similar through appropriate parameter settings. Moreover, the method of time-series forecasting can forecast multiple targets at the same time.

The model used in this study is the classic recurrent neural network (RNN) model with a gating mechanism (Figure 1) - gated recurrent unit (GRU) (Cho, 2014).

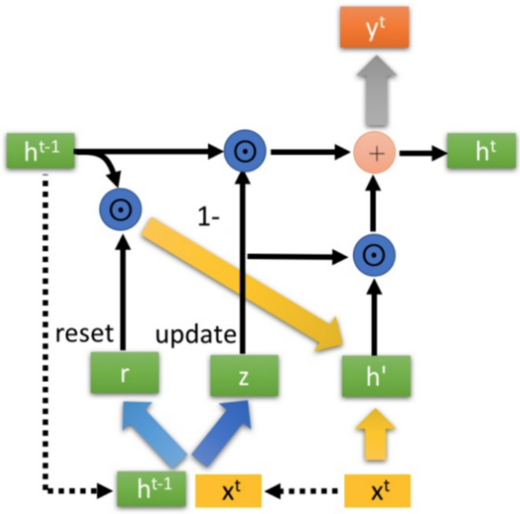

Figure 1 GRU model

Notes: $\odot$ is the Hadamard product operation, x^t and h^t are the input and output vectors, y^t is the output of the GRU, r is th reset gate vector, and z is the update gate vector.

GRU can use fewer parameters than long short-term memory (LSTM). The fundamental reason is that it merges the input gate and forget gate of the original LSTM into one gate, called the update gate. It does not have the division of internal state and external state in LSTM (Zhu, 2021) but directly adds a linear dependency between the state of the current network and the state of the network at the previous moment to solve the problem of gradient disappearance and gradient explosion (Cahuantzi, Roberto et al., 2022) as follows (Daima, 2020):

$$\begin{gathered} r = \sigma(W^r[h^{t-1}, x^t]) \\ z = \sigma(W^r[h^{t-1}, x^t]) \\ h^{t-1'} = r \odot h^{t-1} \\ h' = tanh(Wh^{t-1'}) \\ h^t = (1-z) \odot h^{t-1} + z \odot h' \\ y^t = \sigma(W^y h^t) \end{gathered} \tag{1}$$

where *h'* is the candidate activation vector, σ and *tanh* are sigmoid and hyperbolic tangent activation functions, respectively, and *W* is a parameter matrix.

There are many methods for short-term traffic forecasting. In later a long time, neural network-related calculations have been broadly utilized in different areas, and have been demonstrated to be prevalent to conventional numerical calculations. Among neural network-related algorithms, LSTM is widely used for time series forecasting (Yang et al., 2019).

The computational cost of LSTM is higher, resulting in longer training time. Since LSTM also uses back-time propagation algorithm to update weights, LSTM has disadvantages of back-propagation, such as ReLU unit, gradient burst, and so on. Similar to LSTM, GRU solves the vanishing gradient problem of simple RNNs. However, unlike LSTM, GRU uses fewer gates and does not have a separate internal memory cell state. Therefore, GRU relies entirely on the hidden state as memory, leading to a simpler architecture (Dey & Salem, 2017). The reset gate is responsible for short-term memory, as it determines how much past information is retained and ignored.

The Python library we utilize most is TensorFlow workflow characterized by three distinctive parts to be specific information preprocessing, building model, and preparing demonstrate to form forecasts. The system takes information into multidimensional clusters called tensors and does it in two diverse ways. The most approach is to construct a computational chart to characterize the data flow utilized to prepare the demonstration. The moment and more instinctive approach that is commonly utilized is to utilize enthusiastic execution, which takes after basic programming standards and assesses operations instantly (Prakash et al., 2021). Here is the set of hyperparameter used in my code:

EarlyStopping

This is used to avoid overfitting. In my code I implement it by Keras library's EarlyStopping, and the parameter set was: min_delta (minimum change in loss) to 0.001 and patience to 10 epochs.

GRU Units

For GRU model, I set three different parameter configutions. For the first one is one GRU layer with 50 neurons, the second one is two GRU layers with 150 and 50 neurons, and the third one is three GRU layers with 150, 150 and 50 neurons.

DropOut

Dropout is a technology used to randomly drop out some of input units. It is also used for avoiding overfitting, it is used in the GRU layer and dropout rate is set to 0.2.

Optimizer

I used the stochastic gradient descent optimizer and the learning rate was set as decay=1e-7 and momentum=0.9.

Loss function

The loss function is used to calculate the difference between the predicted values and the true values to measure the performance of the model, RMSE was used.

Epochs

The epochs decides how many times the model will go through my data set. In my code, I set the number of epochs to 50.

3.4 Presentation of Results

The presentation and analysis of the experimental results section aim to give a comprehensive overview of the results obtained from the predictions made by the developed neural network model for IoT-based traffic in smart cities. This section centers on displaying the comes about in a clear and organized way, taken after by an in-depth investigation of the results.

To begin with of all, in arrange to way better get it the substance of the information set, I will visualize the information to begin with, and will show the traffic flow charts of the four junctions, and show them in several time units, so that we are able more instinctively feel the increment in traffic flow and down.

Afterwards, we are going predict the information and show them in three distinctive parameter configurations, and we will see that our anticipated estimate and the genuine values are exceptionally near to each other. This different parameter setup permits us to conduct a comprehensive investigation of all viewpoints of the data set and test the performance of our mode beneath distinctive parameter conditions. These test comes will provide references for assisting the investigation while giving considerable back for decision-making in commonsense applications.

3.4.1 Traffic Flow Trend

First, the traffic flow trend data were transformed into visual information to more intuitively display the changing trend of traffic flow. Figure 2 shows the results of the data transformation to hours, depicting four different patterns corresponding to different junctions. We can see the trend graph of the hour unit, and we can observe the changing pattern of traffic flow at different hours of the day. This can help us understand traffic conditions during peak and trough periods, as well as cyclical changes in traffic flow.

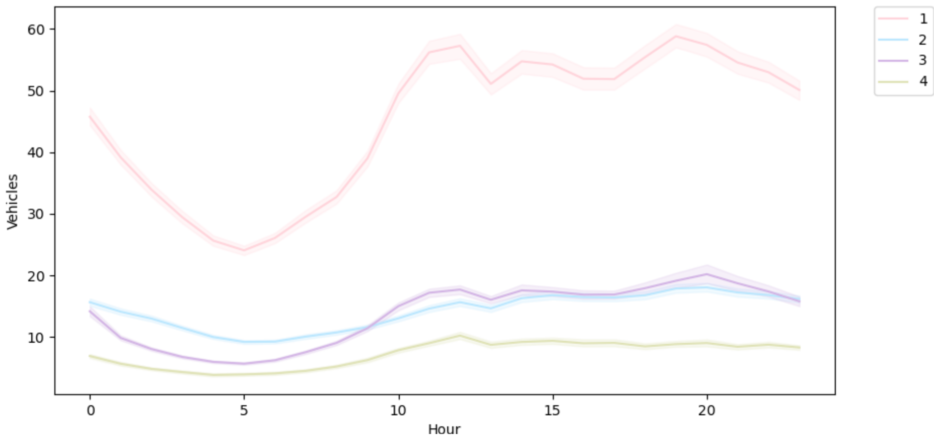

Figure 2 Traffic flow trend by hour for four junctions (1, 2, 3, 4).

We can see that when the common slant rises, it is between 10:00 and 15:00, which appears that this time period is the time when the activity flow is the foremost within the day, and it is additionally the time when it is most likely to cause blockage. Traffic managers can plan ahead based on these observations and deploy at the intersection of the time period to achieve the purpose of quickly clearing the traffic. Of course, ordinary people can also avoid going out during this time period.

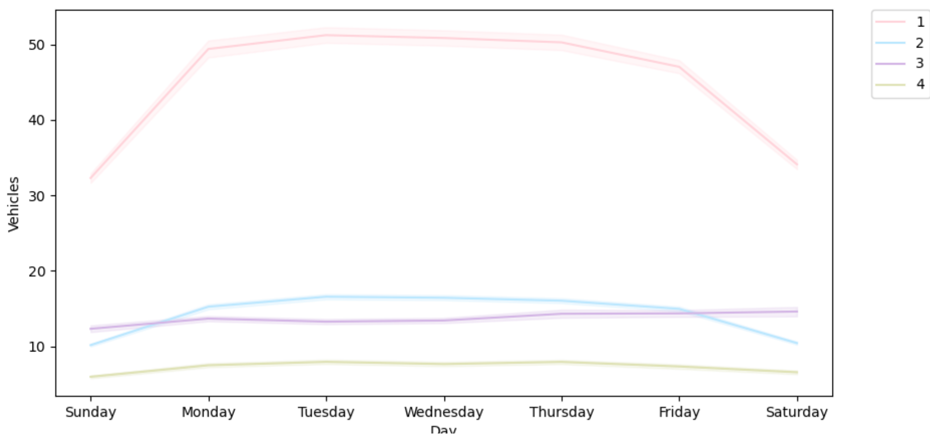

Figure 3 Traffic flow trend by day of week

Figure 3 shows the traffic flow trend change map of the four intersections in daily units. It can moreover be found that inside a week, the trend is more often on the rise from Monday to Friday, and the trend is on the decay on Saturdays and Sundays. Since individuals ordinarily drive to work on weekdays, this provides the validity of my visualization.

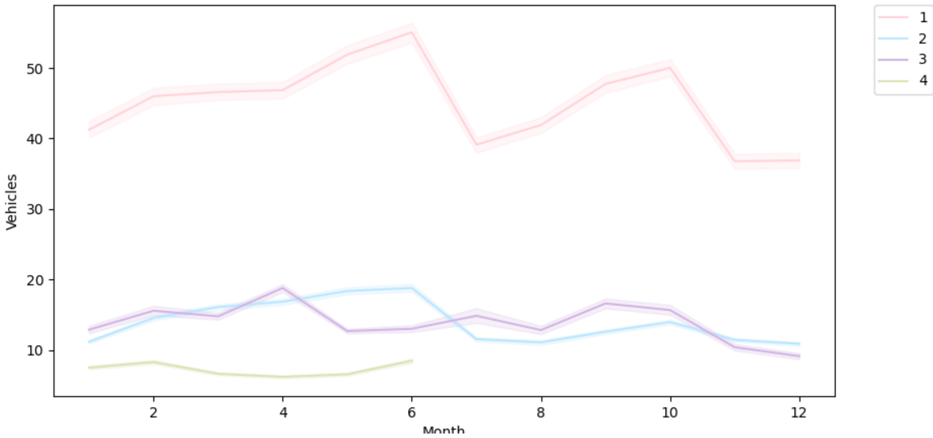

Figure 4 Traffic flow trend by month

Third, monthly trend graphs provide a perspective on long-term trends in traffic flow. We can spot seasonal patterns, average monthly traffic volumes, and possibly annual cyclical variations (Figure 4).

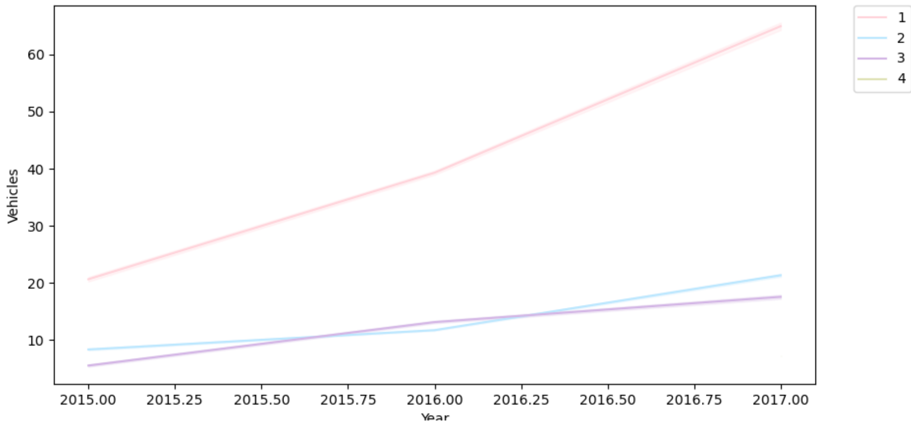

Figure 5 Traffic flow trend by year

Finally, a yearly trend graph reveals the long-term evolution of the traffic flow. By analyzing this chart, able to get it whether the traffic flow appears a changing of expanding or decreasing year by year over time, and the components which will cause this changing.The information reflected in this graph is that the trend of vehicles has been in the rise, the problems that can be explained are the process of urbanization, the increase of population, which leads to the growth of cars (Figure 5).

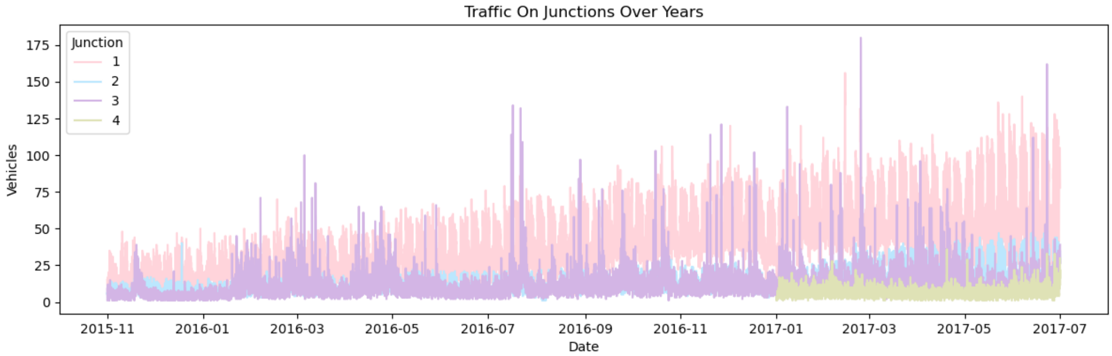

Figure 6 Traffic flow of four junctions

Within the supplementary dataset, we get a chart appearing activity stream patterns over year. This chart (Figure 6) takes the year as the abscissa and the activity stream as the ordinate, appearing the changing drift of activity stream on a long-term time scale.

By looking at this chart, we are ready to uncover the long-term advancement of activity stream. Conceivable designs join year-to-year increases, year-to-year decreases, or changes. This year-level chart can offer assistance us distinguish long-term activity stream designs and patterns for more focused on activity arranging and administration.

By combining perceptions from these charts, we are able get a total understanding of activity, regular varieties, and patterns. long-term improvement. These data are of extraordinary reference esteem for urban activity arranging, activity blockage administration and activity estimating. For example, if we know which season or which month, which day and which time the usual traffic flow is rising, then we can do traffic management in advance to make the city smarter.

3.4.2 Prediction Results

According to different configurations setting, I will figure out if different model setting can effect our predicting results and the performance of the model. It will relate to the layers of GRU model and the number of neurons. My aim is to find out an ideal setting of these parameters, to increase the accurancy and performance of the model and evaluate the influence applied in different junction scenarios.

One layer of the GRU model (50 neurons)

In this model, we will use only one layer of GRU model and set the number of neurons to 50, then my purpose is to test the performance and ability of the computationally effective model. This configuration was used because it considers the balance between the efficiency and complexity of the model. These 50 neurons are associated to each other to make an RNN, and each neuron gets the previous time step input, and after that a new output is created. We can see that Junction 1 has an upward for predicted value and true value trend at the time points of 150, 900, and 1300 (Figure 7), and for Junction 2 that all fluctuations are matched well (Figure 8). But for Junction 3 and Junction 4, the true and predicted values are not matched that well. We will try to analyze what caused it to happen in the analysis of the results (Figure 9, Figure 10).

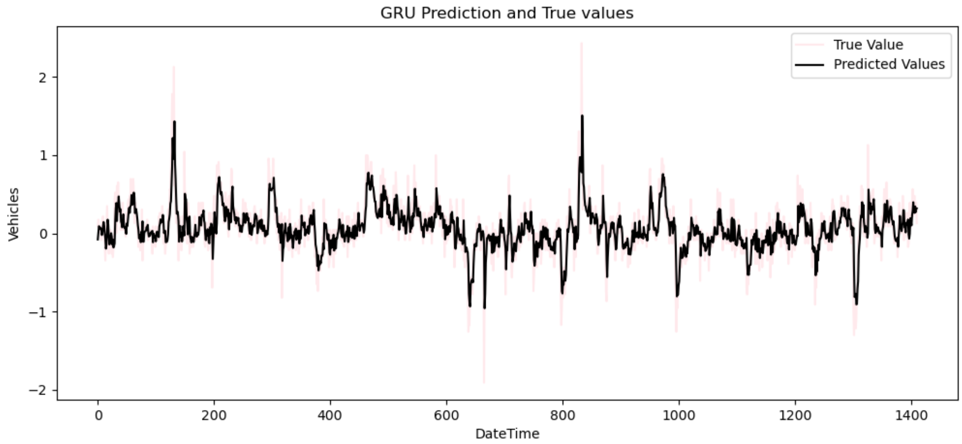

Figure 7 Junction 1 predicted by one-layer GRU model

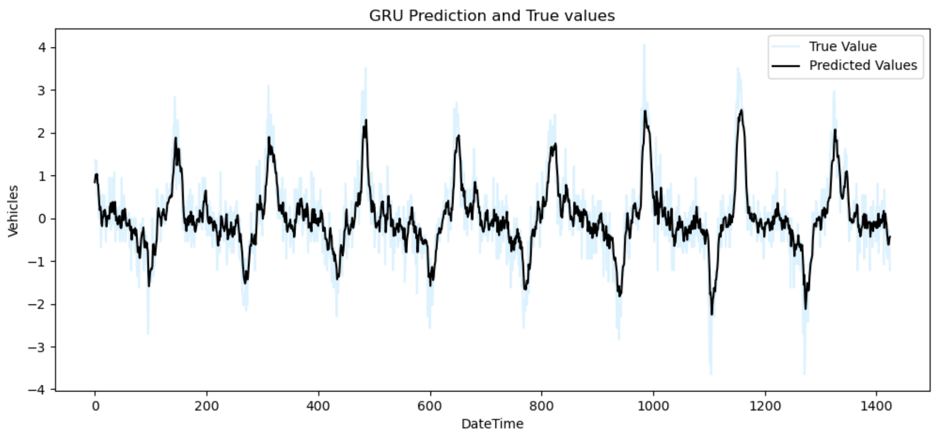

Figure 8 Junction 2 predicted by one-layer GRU model

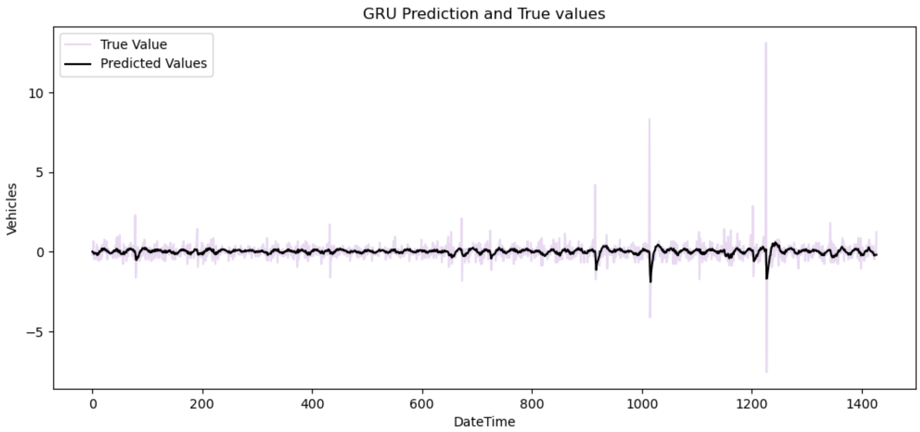

Figure 9 Junction 3 predicted by one-layer GRU model

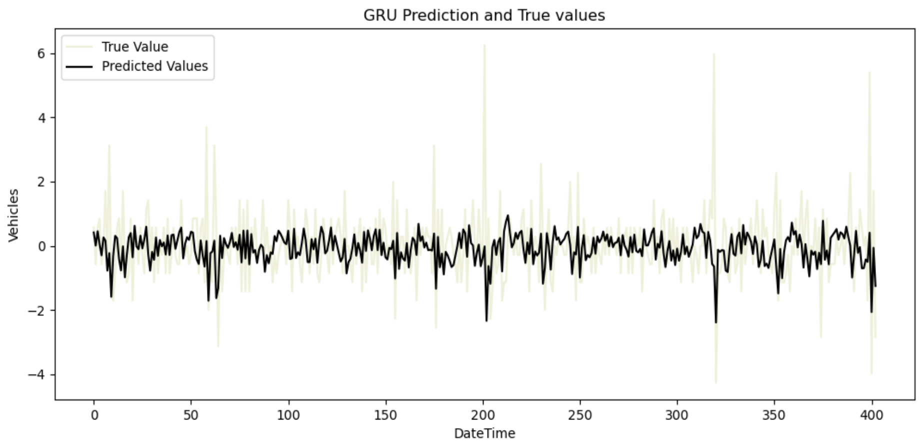

Figure 10 Junction 4 predicted by one-layer GRU model

*Error! Reference source not found.**Two layers of the GRU model (150 and 50 neurons)***

In the second configuration of the GRU model, we are gonna use two layers of the GRU model to predict the traffic flow, the first layer we set to 150 and second layer set to 50 of neurons. By predicting through two layers of neurons, we can increase the accuracy by addional complexity. However, we have almost the same results as for the one GRU layer; that is, for Junction 1 and 2 (Figure 11, Figure 12), the results are very good, but still for Junctions 3 and 4 (Figure 13 and Figure 14) the predictions do not fit well enough.

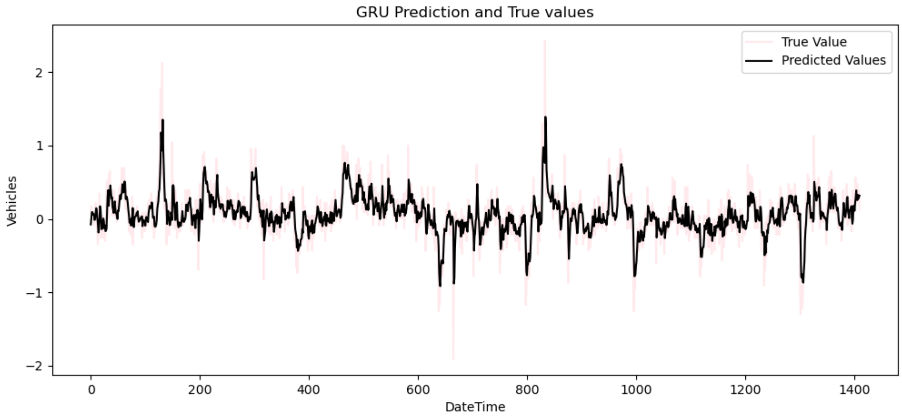

Figure 11 Junction 1 predicted by two-layer GRU model

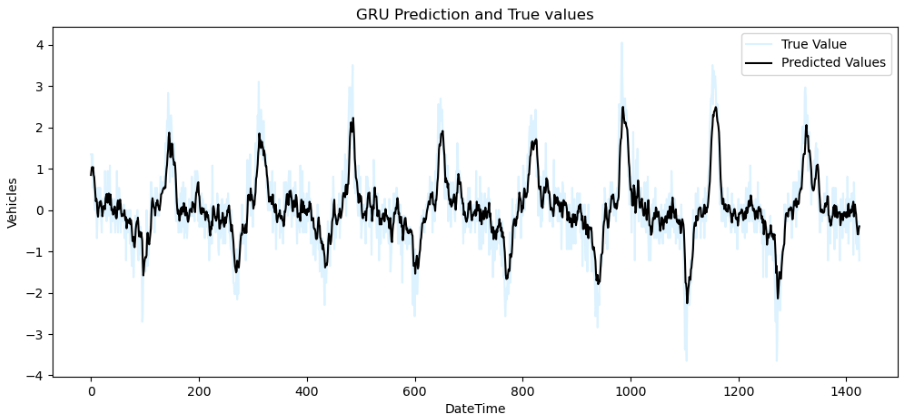

Figure 12 Junction 2 predicted by two-layer GRU model

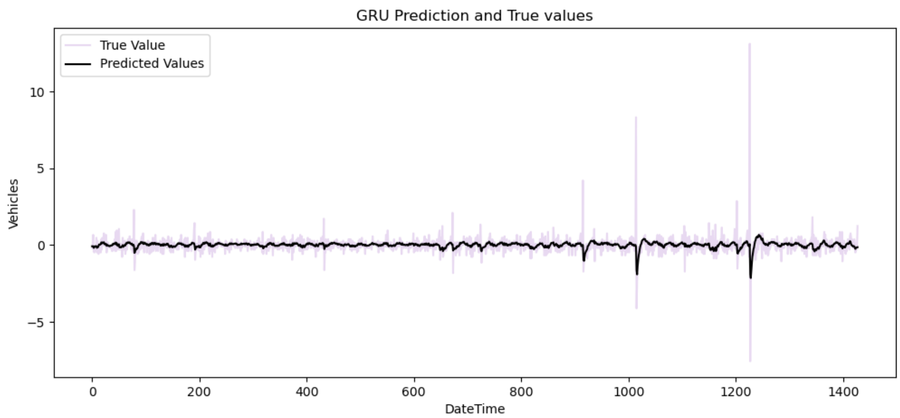

Figure 13 Junction 3 predicted by two-layer GRU model

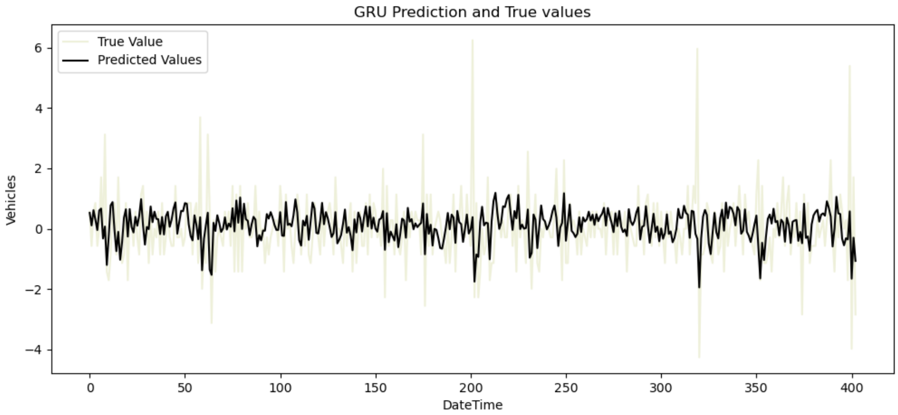

Figure 14 Junction 4 predicted by two-layer GRU model

*Error! Reference source not found.**Three layers of GRU model (150, 150 and 50 number of neurons)***

In the third parameter configuration, we use a three-layer GRU model for traffic situation prediction. So in the details, this GRU model has two layer the neuros was set to 150, one layer was set to 50. The results obtained are basically consistent with our previous two predictions (Figure 15, Figure 16, Figure 17,and Figure 18). For more complex data, such a configuration would definitely improve.

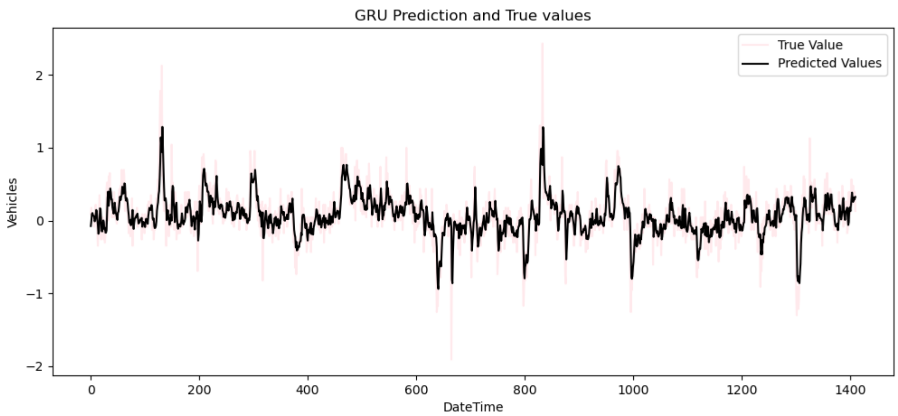

Figure 15 Junction 1 predicted by three-layer GRU model

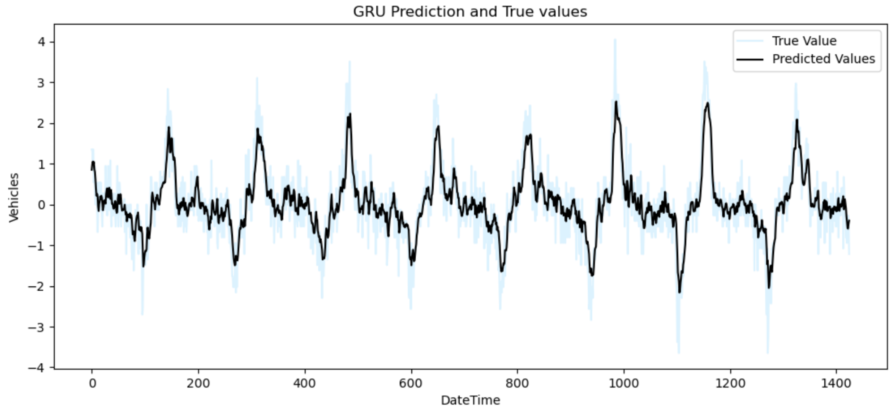

Figure 16 Junction 2 predicted by three-layer GRU model

Figure 17 Junction 3 predicted by three-layer GRU model

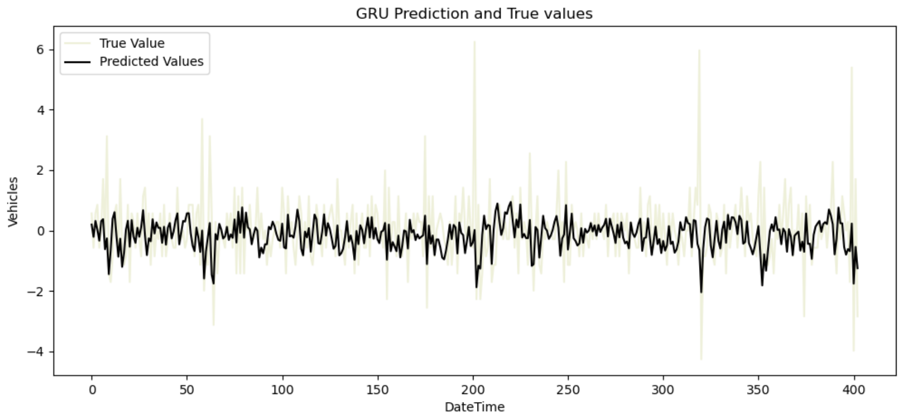

Figure 18 Junction 4 predicted by three-layer GRU model

3.5 Result Analysis

First, we calculate the RMSE values from predicted and actual traffic flow conditions. RMSE is a standard measure of forecast error by calculating the mean of the squares of the differences between the forecast and true values and taking the square root of the result. A smaller RMSE value indicates a better fit between the prediction model and the actual data (Chai, 2014).

Second, we use R^2 to assess the explanatory power and goodness-of-fit of the predictive models. R-squared measures the proportion of actual variability explained by predictions, with values ranging from 0 to 1. A higher R^2 value indicates that the prediction model can well explain the changes in the actual traffic situation and has a better fitting degree.

Finally, we use the MAE to measure the average degree of deviation of the prediction results. MAE can calculate the average value between the forecast and the real value, which can reflect the average error of the forecast model.

One layer of the GRU model

The traffic situation prediction model with the first parameter configuration shows stable and good performance under RMSE, R^2, and MAE indicators. This provides strong support for traffic planning, traffic flow optimization, and decision-making, enabling us to make accurate decisions relying on reliable forecast results**Error! Reference source not found.**).

Table 1 Prediction performance for one-layer GRU model

	Junction 1	Junction 2	Junction 3	Junction 4	Average
RMSE	0.2388	0.5535	0.5910	0.9957	0.5947
R^2	0.5173	0.6799	0.1335	0.2043	0.3838
MAE	0.1727	0.4298	0.2976	0.7092	0.4023

Two layers of the GRU model

We observed very little difference between the predicted results and actual traffic conditions for the second architecture. This shows that the model with the second parameter configuration can accurately capture and predict the changing trend of traffic flow, and has high accuracy**Error! Not a valid bookmark self-reference.**).

Table 2 Prediction performance for two-layer GRU model

	Junction 1	Junction 2	Junction 3	Junction 4	Average
RMSE	0.2397	0.5508	0.5883	0.9809	0.5899
R^2	0.5136	0.6831	0.1412	0.2278	0.3914
MAE	0.1729	0.4288	0.2938	0.7033	0.3996

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Three layers of GRU model

The model with the third parameter configuration can well explain the variability of traffic data. A higher R^2 value indicates that the model can explain most of the variation in the actual data and has a better fit. This further verifies the performance of the model under this parameter configuration**Error! Not a valid bookmark self-reference.**).

Table 3 Prediction performance for three-layer GRU model

	Junction 1	Junction 2	Junction 3	Junction 4	Average
RMSE	0.2427	0.5524	0.5934	0.9862	0.5937
R^2	0.5013	0.6811	0.1264	0.2195	0.3821
MAE	0.1743	0.4288	0.3015	0.6962	0.4002

According to the results we obtained, the traffic situation prediction model with the third parameter configuration shows satisfactory factory performance. The overall comparison of the three configurations is presented in Table 4, showing that the two-layer architecture performed best in terms of RMSE and MAE, while the highest R^2 was achieved by the three-layer GRU model. We can also see from the above tables that for Junctions 3 and 4, any GRU model provided high RMSE values. This seems to be attributed to (1) missing patterns in the data with a high volatility of the number of vehicles, and (2) less data available for Junction 4, so the training process is limited.

Table 4 Average prediction performance for different GRU models

	One-layer	Two-layer	Three-layer
RMSE	0.5947	**0.5899**	0.5937
R^2	0.3838	0.3914	**0.3821**
MAE	0.4023	**0.3996**	0.4002

3.6 Reliability and Limitations

First, the robustness of the model is limited by the quality and reliability of the dataset used. If there is noise, missing values, or outliers in the dataset, it can affect the certainty and predictability of the model. Therefore, in the data collection and preprocessing stage, it is necessary to use appropriate methods to clean and process the data to ensure the quality and reliability of the data. Second, the durability of neural network models is also affected by the choice of hyperparameters during training. Different hyperparameter instrumentation settings can lead to differences in model performance. Therefore, in the process of model training and verification, cross-validation and parameter tuning are required to obtain the best combination of hyperparameters and ensure that the model has good robustness. In addition, the robustness of the model also depends on the representativeness of the dataset. If a data set includes a particular region or period, the predictive power of the model in other regions or periods may be limited. When applying the model to other cities or periods, the model should be migrated appropriately to ensure the robustness and universality of the model.

As deep learning matures and new technologies develop, its ability to process data also grows, major research institutions and technology giants have invested a lot of money and energy in the field of deep learning, and have achieved amazing achievements. Deep learning has significant disadvantages, such as that its performance improvement depends on the amount of data supplied. The more data provided for training, the greater the improvement, and vice versa.

4 Conclusion

4.1 Summary of Findings

This section summarizes the research results according to the evaluation results of different parameter configurations for predicting traffic conditions.

First, the study used a data set consisting of traffic data collected from four intersections. Data are processed and transformed into a format suitable for analysis and prediction. The traffic conditions at these intersections are predicted using a GRU model with three different parameter configurations. The first configuration involves a single-layer GRU model with 50 neurons, while the second configuration includes a two-layer GRU model with 150 and 50 neurons, respectively. Finally, the third configuration uses a three-layer GRU model, where two layers consist of 150 neurons and one layer consists of 50 neurons. Evaluation metrics including RMSE, R^2, and MAE are used to evaluate the performance of each parameter configuration.

The results show that the first parameter configuration exhibits stable performance with comparable RMSE, R^2 and MAE values. This configuration demonstrates the ability to accurately capture and predict traffic trends at intersections. The second parameter configuration employs a two-layer GRU, showing consistently good performance on all evaluation metrics. These predictions are accurate and closely related to actual traffic conditions. The third parameter configuration uses a three-layer GRU model, with encouraging results. The predictions showed high accuracy and effectively captured the underlying patterns in the traffic data. The results show that the adopted GRU model with different parameter configurations has proven its effectiveness in predicting traffic conditions at the studied intersections. These models exhibit stable and satisfactory performance, providing reliable insights for traffic planning, optimization, and decision-making processes.

4.2 Practical Implications

First, according to my research, we can apply the developed parameter configuration and prediction models to improve the efficiency and accuracy of traffic management. By accurately predicting traffic trends, traffic managers can better plan road use, signal timing, and traffic control strategies. This reduces traffic congestion, improves road efficiency, and provides a more reliable travel experience. Second, using my research results, we can develop more targeted transportation planning strategies.

This work using neural networks to predict IoT-based traffic in smart cities makes a significant contribution to the fields of traffic management and urban planning. By harnessing the power of neural networks and incorporating IoT data, the proposed traffic prediction system exhibits higher accuracy and reliability in predicting traffic patterns. The preprocessing techniques employed in this study ensured the quality and reliability of the input data and facilitated the overall performance of the framework.

To sum up, the research on using neural networks to predict the traffic volume based on the IoT in smart cities is of great significance for traffic management, urban planning, and the development of intelligent transportation systems. With continued advances in data collection, machine learning techniques, and integration with smart infrastructure, the potential to improve traffic forecasting and management in smart cities is enormous. This is an exciting and growing field with great potential for creating more efficient, sustainable, and liveable urban environments.

4.3 Future Research Directions

AI systems will bring about greater changes in the future of society and improve people's daily lives. Looking ahead, there are several potential future developments in this field:

- Autonomous vehicles: Encourage investigate can center on progressing the effectiveness, security, and integration of associated and independent vehicles.
- Smart traffic administration: Creating smart traffic administration frameworks that use real-time information from sensors, cameras, and associated vehicles can offer assistance optimize traffic flow, decrease clog, and make strides transportation effectiveness.
- Smart framework: Exploring the integration of keen advances into transportation framework, such as keen activity lights, keen stopping frameworks, and brilliantly street signage, can contribute to more proficient and feasible transportation systems.
- Transportation information analytics: Progressing information analytics procedures can empower superior investigation and utilization of large-scale transportation information. This incorporates creating models for prescient analytics, request estimating, and real-

time decision-making to optimize transportation operations and improve client encounter.

These investigate bearings point to address the challenges and openings within the domain of savvy transportation, clearing the way for more proficient, maintainable, and user-centric transportation frameworks within the future.

References

[1] AREM, B. V., VAN DRIEL, C. J. G. and VISSER, R. The impact of cooperative adaptive cruise control on traffic-flow characteristics. *IEEE Transactions on Intelligent Transportation Systems*. 2006. Vol. 7, No. 4, p. 429–436.

[2] AZGOMI, Hamid Fekri and JAMSHIDI, Mo. A brief survey on smart community and smart transportation. *2018 IEEE 30th International Conference on Tools with Artificial Intelligence (ICTAI)*. 2018. p. 932–939. DOI: 10.1109/ictai.2018.00144.

[3] BELLI, Laura, CILFONE, Antonio, DAVOLI, Luca, FERRARI, Gianluigi, ADORNI, Paolo, DI NOCERA, Francesco, DALL'OLIO, Alessandro, PELLEGRINI, Cristina, MORDACCI, Marco and BERTOLOTTI, Enzo. IoT-Enabled Smart Sustainable Cities: Challenges and Approaches. *Smart Cities*. 2020. Vol. 3, No. 3, p. 1039–1071.

[4] CAHUANTZI, Roberto, CHEN, Xinye, and Stefan GÜTTEL. A comparison of LSTM and GRU networks for learning symbolic sequences. *ArXiv*, 2021. Retrieved June 27, 2023 from https://arxiv.org/abs/2107.02248.

[5] CHAI, T. and DRAXLER, R. R. Root mean square error (RMSE) or mean absolute error (mae)? – arguments against avoiding RMSE in the literature. *Geoscientific Model Development*. 2014. Vol. 7, No. 3, p. 1247–1250. DOI: 10.5194/gmd-7-1247-2014.

[6] CHO, Kyunghyun, VAN MERRIENBOER, Bart, GULCEHRE, Caglar, BAHDANAU, Dzmitry, BOUGARES, Fethi, SCHWENK, Holger and BENGIO, Yoshua. Learning phrase representations using RNN encoder–decoder for statistical machine translation. *Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP)*. 2014. DOI: 10.3115/v1/d14-1179.

[7] DAI, G., MA C. and X. XU. Short-term traffic flow prediction method for urban road sections based on space–time analysis and GRU. *IEEE Access*. 2019. Vol. 7, p. 143025–143035, DOI: 10.1109/ACCESS.2019.2941280.

[8] DAMERI, Renata Paola. Searching for smart city definition: A comprehensive proposal. *International Journal of Computers & Technology*. 2013. Vol. 11, No. 5, p. 2544–2551. DOI: 10.24297/ijct.v11i5.1142.

[9] DEY, Rahul and SALEM, Fathi M. Gate-variants of gated recurrent unit (GRU) neural networks. *2017 IEEE 60th International Midwest Symposium on Circuits and Systems (MWSCAS)*. 2017. P. 1597-1600. DOI: 10.1109/mwscas.2017.8053243.

[10] DIWAKAR BABU, Pavan Teja. Methodologies for traffic congestion prediction for a IOT based smart city using machine learning and CNN. *SSRN Electronic Journal*. 2019. DOI: 10.2139/ssrn.3510057.

[11] HAMZA, M. *These are the top 20 sustainable smart cities in the world from 2021*. Retrieved 27-06-2023, from https://www.disruptive-technologies.com/blog/the-top-20-sustainable-smart-cities-in-the-world.

[12] JABAMONY, Jalaney and SHANMUGAVEL, Ganesh Ramaswamy. IoT based bus arrival time prediction using Artificial neural network (ANN) for smart public Transport System (SPTS). *International Journal of Intelligent Engineering & Systems*, 2020. Vol. 13, No. 1. p. 312–323.

[13] JOSHI, Sujata, SAXENA, Saksham, GODBOLE, Tanvi and SHREYA. Developing smart cities: An integrated framework. *Procedia Computer Science*. 2016. Vol. 93, p. 902–909. DOI: 10.1016/j.procs.2016.07.258.

[14] KASHYAP, Anirudh Ameya, RAVIRAJ, Shravan, DEVARAKONDA, Ananya, NAYAK K, Shamanth R, K V, Santhosh and BHAT, Soumya J. Traffic flow prediction models – a review of deep learning techniques. *Cogent Engineering*. 2022. Vol. 9, No. 1, p. 2010510. DOI: 10.1080/23311916.2021.2010510.

[15] KOUMETIO TEKOUABOU, Stéphane Cédric, ABDELLAOUI ALAOUI, El Arbi, CHERIF, Walid and SILKAN, Hassan. Improving parking availability prediction in smart cities with IOT and ensemble-based model. Journal of King Saud University - Computer and Information Sciences. 2022. Vol. 34, No. 3, p. 687–697. DOI: 10.1016/j.jksuci.2020.01.008.

[16] MADAKAM, Somayya, RAMASWAMY, R and TRIPATHI, Siddharth. Internet of Things (IoT): A Literature Review. *Journal of Computer and Communications*. 2015. Vol. 3, No. 05, p. 164–173. DOI: 10.4236/jcc.2015.35021.

[17] MORIYA, Bhavin, Traffic prediction: GRU, 2021. Retrieved 27-06-2023 from www.kaggle.com/code/bhavinmoriya/traffic-prediction-gru/notebook.

[18] NI, Daiheng. Limitations of current traffic models and strategies to address them. *Simulation Modelling Practice and Theory*. 2020. Vol. 104, p. 102137. DOI: 10.1016/j.simpat.2020.102137.

[19] OLADIMEJI, Damilola, GUPTA, Khushi, KOSE, Nuri Alperen, GUNDOGAN, Kubra, GE, Linqiang and LIANG, Fan. Smart transportation: An overview of technologies and applications. *Sensors*. 2023. Vol. 23, No. 8, p. 3880.

[20] OLUSHOLA, Omoyiola Bayo. Factors affecting IoT adoption. *IOSR Journal of Computer Engineering*. 2019. Vol. 21, No. 6, p. 19–24. DOI: 10.9790/0661-2106011924.

[21] PRAKASH, Kolla Bhanu, RUWALI, Adarsha and KANAGACHIDAMBARESAN, G. R. *Introduction to tensorflow package. Programming with TensorFlow*. 2021. P. 1–4. DOI: 10.1007/978-3-030-57077-4_1.

[22] QIU, Junfei, WU, Qihui, DING, Guoru, XU, Yuhua, and SHUO Feng. A survey of machine learning for big data processing. *EURASIP Journal on Advances in Signal Processing*. 2016. Vol. 1, p. 1–16. DOI: 10.1186/s13634-016-0355-x.

[23] SMYS, S., ZONG CHEN, Joy Iong and SHAKYA, Subarna. Survey on neural network architectures with deep learning. *Journal of Soft Computing Paradigm*. 2020. Vol. 2, No. 3, p. 186–194. DOI: 10.36548/jscp.2020.3.007.

[24] YANG, Bailin, SUN, Shulin, LI, Jianyuan, LIN, Xianxuan and TIAN, Yan. Traffic flow prediction using LSTM with feature enhancement. *Neurocomputing*. 2019. Vol. 332, p. 320–327. DOI: 10.1016/j.neucom.2018.12.016.

[25] ZHU, Di, LIU, Yu, YAO, Xin and FISCHER, Manfred M. Spatial regression graph convolutional neural networks: A deep learning paradigm for spatial multivariate distributions. *GeoInformatica*. 2021. Vol. 26, No. 4, p. 645–676. DOI: 10.1007/s10707-021-00454-x.

Appendix A: Python Source Code

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import datetime
import tensorflow
from statsmodels.tsa.stattools import adfuller
from sklearn.preprocessing import MinMaxScaler
from tensorflow import keras
from keras import callbacks
from tensorflow.keras import Sequential
from tensorflow.keras.layers import Conv2D, Flatten, Dense, LSTM, Dropout, GRU, Bidirectional
from tensorflow.keras.optimizers import SGD
import math
from sklearn.metrics import mean_squared_error
import warnings
```

Import libraries

```
data = pd.read_csv("traffic.csv")
data["DateTime"]= pd.to_datetime(data["DateTime"])
data = data.drop(["ID"], axis=1) #dropping IDs
df=data.copy()
colors = [ "#FFD4DB","#BBE7FE","#D3B5E5","#dfe2b6"]
plt.figure(figsize=(20,4),facecolor="#ffffff")
Time_series=sns.lineplot(x=df['DateTime'],y="Vehicles",data=df, hue="Junction", palette=colors)
Time_series.set_title("Traffic On Junctions Over Years")
Time_series.set_ylabel("Vehicles")
Time_series.set_xlabel("Date")
```

Loading and exploring data

```
df["Year"]= df['DateTime'].dt.year
df["Month"]= df['DateTime'].dt.month
df["Date_no"]= df['DateTime'].dt.day
df["Hour"]= df['DateTime'].dt.hour
df["Day"]= df.DateTime.dt.strftime("%A")
```

Split features using DataTime

```
def Normalize(df,col):
    average = df[col].mean()
    stdev = df[col].std()
    df_normalized = (df[col] - average) / stdev
    df_normalized = df_normalized.to_frame()
    return df_normalized, average, stdev

def Difference(df,col, interval):
    diff = []
    for i in range(interval, len(df)):
        value = df[col][i] - df[col][i - interval]
        diff.append(value)
    return diff
```

Function for data transformation

```
df_N1, av_J1, std_J1 = Normalize(df_1, "Vehicles")
Diff_1 = Difference(df_N1, col="Vehicles", interval=(24*7)) # a week's diffrence
df_N1 = df_N1[24*7:]
df_N1.columns = ["Norm"]
df_N1["Diff"]= Diff_1

df_N2, av_J2, std_J2 = Normalize(df_2, "Vehicles")
Diff_2 = Difference(df_N2, col="Vehicles", interval=(24)) # a day's diffrence
df_N2 = df_N2[24:]
df_N2.columns = ["Norm"]
df_N2["Diff"]= Diff_2

df_N3, av_J3, std_J3 = Normalize(df_3, "Vehicles")
Diff_3 = Difference(df_N3, col="Vehicles", interval=1) # an hour's diffrence
df_N3 = df_N3[1:]
df_N3.columns = ["Norm"]
df_N3["Diff"]= Diff_3

df_N4, av_J4, std_J4 = Normalize(df_4, "Vehicles")
Diff_4 = Difference(df_N4, col="Vehicles", interval=1) # an hour's diffrence
df_N4 = df_N4[1:]
df_N4.columns = ["Norm"]
df_N4["Diff"]= Diff_4

Sub_Plots4(df_N1.Diff, df_N2.Diff,df_N3.Diff,df_N4.Diff,"Dataframes After Transformation")
```

Data transformation

```
def Split_data(df):
    training_size = int(len(df)*0.90)
    data_len = len(df)
    train, test = df[0:training_size],df[training_size:data_len]
    train, test = train.values.reshape(-1, 1), test.values.reshape(-1, 1)
    return train, test
J1_train, J1_test = Split_data(df_J1)
J2_train, J2_test = Split_data(df_J2)
J3_train, J3_test = Split_data(df_J3)
J4_train, J4_test = Split_data(df_J4)
```

Splitting data into training and test set

```
def GRU_model(X_Train, y_Train, X_Test):
    early_stopping = callbacks.EarlyStopping(min_delta=0.001, patience=10, restore_best_weights=True)
    # callback delta 0.01 may interrupt the learning, could eliminate this step, but meh!

    # The GRU model
    model = Sequential()
    model.add(GRU(units=150, return_sequences=True, input_shape=(X_Train.shape[1], 1), activation='tanh'))
    model.add(Dropout(0.2))

    model.add(GRU(units=150, return_sequences=True, input_shape=(X_Train.shape[1], 1), activation='tanh'))
    model.add(Dropout(0.2))

    model.add(GRU(units=50, input_shape=(X_Train.shape[1], 1), activation='tanh'))
    model.add(Dropout(0.2))
    model.add(Dense(units=1))

    # Compiling the model
    model.compile(optimizer=SGD(decay=1e-7, momentum=0.9), loss='mean_squared_error')
    model.fit(X_Train, y_Train, epochs=50, batch_size=150, callbacks=[early_stopping])
    pred_GRU = model.predict(X_Test)
    return pred_GRU
```

Model development

```
from sklearn.metrics import r2_score # R square
r2_J1=r2_score(y_testJ1,PredJ1)
r2_J2=r2_score(y_testJ2,PredJ2)
r2_J3=r2_score(y_testJ3,PredJ3)
r2_J4=r2_score(y_testJ4,PredJ4)

from sklearn import metrics # MAE
def mae(y_true, y_pred):
    res_mae = metrics.mean_absolute_error(y_true, y_pred)
    return res_mae
print('mae:',mae(y_testJ4,PredJ4))

def RMSE_Value(test, predicted):
    rmse = math.sqrt(mean_squared_error(test, predicted))
    print("The root mean squared error is {}.".format(rmse))
    return rmse
```

Showing results