Scalable Computing: Practice and Experience, ISSN 1895-1767, http://www.scpe.org
© 2024 SCPE. Volume 25, Issues 6, pp. 5441–5450, DOI 10.12694/scpe.v25i6.3326

A SHARED ECONOMY DATA PREDICTION MODEL BASED ON DEEP LEARNING

MIN ZHOU*

Abstract. In the dynamic and intricate shared economy, efficient resource management and forecasting are still crucial. In this research, a new prediction model is presented that aims to improve the operational efficiency of several shared economy services. Our method creatively combines Long Short-Term Memory (LSTM) networks with Genetic Algorithms (GA) to assess user demand and optimize resource deployment. We apply this methodology especially to e-scooter sharing services, but the underlying ideas and methods can be applied to other shared economy platforms as well, like peer-to-peer lending services, car sharing, and vacation rentals. The model starts with a GA to adjust the hyperparameters of the LSTM network, making the network better suited to handle specific characteristics of common economic data. Capturing the complex temporal and spatial patterns of user behavior and demand on these platforms requires this optimization. The LSTM element then predicts changes in service demand due to its capacity to analyze sequential records. Further to being useful for analyzing sequential data and predicting destiny wishes, this predictive functionality is important for a shared economy platform to correctly manage stock, allocate assets, and predict personal wishes. We use a large dataset to check our technique, demonstrating the predictive accuracy of the model and demand and its potential to aid strategic choice-making. Compared to traditional fashions, the consequences show a large development in forecast accuracy and resource allocation efficiency. Our methodology creates a robust basis for statistics-driven insights that decorate customer happiness and decorate the long-term increase of the shared financial system. This work highlights the blended ability of GA and LSTM inside the shared economy and paves the manner for future enhancements in using modern-day gadget mastering techniques to optimize and alter various shared services. In quick, effective useful resource control and forecasting in the shared economic system is tough, however our specific forecasting model combining GA-LSTM gives a manner ahead. Our technique, as it should be, predicts fluctuations in provider demand; it was first refined the usage of GA to regulate the LSTM hyperparameters. The consequences show how correct and powerful our version is and spotlight how it can enhance customer pleasure and operational performance. This research paves the manner for future trends within the software of gadgets, gaining knowledge of methods and supports the continuing enlargement and development of shared economic system offerings.

Key words: Shared economy, resource allocation, GA, LSTM, demand prediction, operational efficiency.

1. Introduction. The shared financial system has turn out to be a disruptive commercial enterprise paradigm this is converting how services are supplied and sources are used[5, 25]. This financial model, that is characterised through peer-to-peer trading and collaborative intake, is relevant to a number of industries, including commodities sharing, lodging, and transportation. Green useful resource allocation is crucial to this versions achievement and depends on particular person call for forecasting [2]. The shared financial system is dynamic in comparison to standard employer fashions with call for fluctuations impacted by way of an extensive variety of variables, together with time, vicinity, person choices, and socioeconomic developments [22, 24]. This variability creates a large hassle: how to make certain that assets are allocated as effectively as feasible to fulfill customer call for without developing shortage or oversupply? Sophisticated predictive models which can discover complicated patterns in big datasets and offer useful insights for aid allocation are required to satisfy this task.

There are hopeful answers to those issues inside the quickly developing fields of information science and device studying. With the usage of state-of-the-art algorithms, predictive analytics can forecast call for via reading the big volumes of information produced with the aid of shared economic system platforms. However, the nonlinearities and temporal correlations that characterize shared economy facts are every so often too complex for classic statistical procedures to fully capture. That is in which deep studying strategies, specifically those based on neural networks are useful. Recurrent neural networks (RNN) namely LSTM networks have tested giant potential [16, 1, 26]. Their proficiency in handling sequential information makes them ideal for examining time-series information, inclusive of demand styles in the shared financial system over an extended

*School of Finance and Accounting, Anhui Sanlian University, Hefei, Anhui, 230000, China (minzhouresead@outlook.com)

time frame[19, 9]. However configuring LSTM networks optimally for a given software continues to be a tough venture that often necessitates a outstanding deal of trial and error [3, 18, 14].

The choice of appropriate hyperparameters is a crucial element within the implementation of deep gaining knowledge of models. The model's performance is substantially impacted with the aid of this preference, which is a difficult venture considering the massive hyperparameter space. GA can be quite vital in this situation. Natural selection serves as the model for the optimization techniques utilized by GA [4, 23]. To determine the proper parameters for a specific version they can speedy and correctly search throughout huge solution areas. GA iteratively regulate the hyperparameters merging and enhancing them to locate the most perfect configuration by mimicking the process of evolution. This method could be very helpful for optimizing deep studying models as an appropriate selection of hyperparameters can substantially improve version overall performance[20, 11].

Through the evaluation we present a brand-new method that combines the strong time-series records processing energy of LSTM with GA understanding in hyperparameter optimization. Specifically designed for the shared economy enterprise this GA-LSTM model targets to transform demand forecast and resource allocation [7, 13, 17]. By the software of GA the structure and parameters of the LSTM network are optimized permitting the model to forecast user demand styles with extra accuracy. The version can now as it should be constitute the complicated temporal dynamics and nonlinear interactions seen in shared financial system statistics thanks to this optimization. Consequently, the recommended GA-LSTM version represents a strategic device in addition to a generation improvement for shared financial system systems, empowering them to make information-pushed selections that growth person pleasure, lower costs, and improve operational performance. This innovative approach establishes a general for next predictive analytics products in this discipline and expands the usage of deep learning within the shared financial system.

Efficient resource management and precise demand forecasting are essential in the ever-changing shared economy, where services like car sharing, peer-to-peer financing, e-scooter sharing, and holiday rentals are becoming more and more popular. These platforms operate in environments with complex user behaviors and dynamic demand patterns, which makes it difficult to optimize resource deployment in a way that successfully meets user needs. To tackle this issue, we present a novel prediction model that aims to improve the operational effectiveness of several shared economy services.

The primary contributions of the study are:

1. On these studies a novel aggregate of LSTM networks and GA is provided specially designed for the shared economic system industry. This hybrid model makes use of GA to improve LSTM configurations enhancing prediction efficiency and accuracy.
2. Across these studies we especially awareness the E-scooter area. We provide an advanced demand prediction model that correctly forecasts user call for patterns throughout multiple shared economic system systems. The dynamic and complex nature of shared financial system statistics is effortlessly dealt with via this model, which significantly complements resource allocation processes.
3. Our study showcases the green software of Genetic Algorithms in deep gaining knowledge of version hyperparameter adjustment. This method streamlines the performance of the LSTM community and makes the generally difficult technique of version configuration less complicated.
4. The shared economy is supported with the aid of empirical proof, which the thing uses to validate its sensible and scalable methodology. Our version demonstrates how it can be used to many shared economy industries imparting a flexible device for organizations to improve purchaser delight and operational performance.

2. Related Work. The impact that private trip-hailing services like Uber and Lyft have had when you consider that their launch in 2011 and 2012 on the United States transportation atmosphere is the primary topic of this examine [6]. The continuously changing landscape of recent mobility offerings provides issues for transportation making plans and regulation, that are mentioned in this article. This observe makes a tremendous addition by providing clean statistics and perspectives on the uptake and first attitudes of shared e-scooters which experienced a pointy upward push in non-public investment. The comprehensive ballot, which become finished in 11 principal cities, gives insightful records about public opinion. It emphasizes favorable evaluations, particularly amongst ladies and decrease-class demographics, and greater gender parity compared to traditional docked bikesharing structures. The paper [8] looks at assesses how shared e-scooter systems, which were first added in 2017, in shape into the ecu Sustainable and clever Mobility approach and how they make a contribution to sustainable city mobility. The paper emphasizes the environmental advantages, together with decreased air pollutants and greater mobility resilience, especially noteworthy all through the Covid-19 pandemic, through a thorough literature analysis and a case observe in Braga. The examine emphasizes how nicely e-scooters paintings to encourage social separation and reduce reliance on private vehicles for quick-distance journey. Following the outbreak, Braga's persevered reliance on e-scooters and the implementation of discounted prices to sell use highlight the machine's viability and acceptance. The sudden upward push in reputation of shared, dockless electric powered kick scooters inside the United States of America at some stage in 2017 is tested [10]. The dockless characteristic, which enables users to go away scooters at any location, highlights the power and ease of those battery-powered cars as an opportunity to more traditional types of transportation. The have a look at highlights how these firms, which give quick-term rentals and add to the micro-mobility scene, are for-earnings. The have a look at gives a thorough analysis of the shared scooter phenomena, emphasizing its sensible features in addition to the unique possibilities and troubles they present in city environments. This indicates a dramatic trade in the manner city human beings cross about quick distances.

The paper [21] takes a look at explores the growing phenomenon of micromobility with a particular emphasis on e-scooters in Thessaloniki, Greece. Surveys are utilized to evaluate person attitudes and moves, and the outcomes display that e-scooters are more often used for enjoyment than for transportation. The look at draws attention to how common e-scooters are on each motorcycle lanes and non-bike lanes. The actions of vehicles and the requirement for added bike lanes to promote the use of e-scooters are the primary troubles stopping their usage. Whilst evaluations approximately e-scooters are largely comparable throughout special demographics, the examine additionally observes modest versions in utilization based on age and gender. Those findings offer vital insights into the combination of e-scooters in city mobility. The paper [7] makes use of advanced device gaining knowledge of strategies to estimate PM2.Five concentrations with a purpose to deal with China's growing air pollutants problem. In an effort to extract functions from air great data, it makes use of intense gradient lifting (XGBoost) along with a multi-scale convolutional neural community (MSCNN) to extract spatial-temporal function relations. The XGBoost-MSCGL model that has been cautioned combines the benefits of XGBoost, MSCNN, and LSTM and is more suitable via Genetic Algorithms (GA) to offer correct PM2.5 prediction. Complete pollutants and weather records from the Fen-Wei undeniable are used to validate the model's efficacy. The outcomes show off noteworthy improvements in forecast precision and applicability while juxtaposed with reference fashions, demonstrating the version's effectiveness in tackling environmental troubles. We can estimate copper charges with this techniques gives a unique GA-LSTM with an error correction approach, addressing the elaborate marketplace adjustments [15]. The model creates a hybrid input that improves forecast accuracy via deliberating both past developments and causality. It does this with the aid of combining latest information on copper charges with precise influencing elements. After being evaluated for generalizability with iron ore expenses and demonstrated using a 30-year records series of copper costs, the version outperforms benchmark fashions. This novel method demonstrates the version's resilience and capacity for generalization, which makes it an crucial device for monetary forecasting, especially in erratic commodities markets inclusive of the ones for copper.

3. Methodology.

3.1. Proposed Methodology Overview. This segment introduces the advised GA-LSTM method that proven in Figure 3.1. The method have a look at is changed to concentrate on e-scooter utilization prediction and deployment optimization. This variation is critical for managing with the precise difficulties offered by this shared economy provider along with maintaining availability, optimizing preservation and recharging schedules and striking a balance among supply and demand. First, we gather full-size utilization data on e-scooters which includes journey begin and end times, locations, distances and consumer demographics. Contextual statistics that could affect using e-scooters is added to this series, inclusive of weather reviews, statistics on parking spaces and motorcycle lanes and statistics on special activities. Preprocessing is performed at the accumulated records to make certain it is prepared for analysis. This encompass normalizing the statistics to a not unusual format segmenting it into applicable time frames and cleaning the information to do away

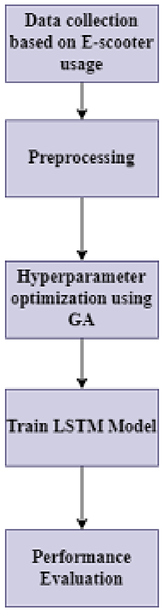

Fig. 3.1: Proposed GA-LSTM Architecture

with any errors or inconsistencies. To ensure the LSTM model can examine the data successfully. The LSTM networks hyperparameters are then optimized for the e-scooter dataset the usage of genetic algorithms. The GA iteratively looks for the exceptional series of parameters which includes gaining knowledge of rate, range of layers and neurons in every layer and other pertinent LSTM settings. Improving the models potential to precisely forecast e-scooter demand styles requires this optimization. With the optimized hyperparameters we continue to teach the LSTM version using the preprocessed e-scooter information. This schooling allows the version to study from ancient utilization styles and identify traits which might be predictive of future e-scooter demand. Eventually, the trained GA-LSTM model is carefully tested and confirmed using separate datasets to assess its predictive accuracy and generalizability. This step guarantees that the model can reliably forecast e-scooter call for in numerous situations and places additionally making it a practical device for e-scooter carrier vendors.

3.2. Proposed GA-LSTM Workflow.

3.2.1. GA based Hyperparameter Tuning. In shared financial system the performance of GA coupled with LSTM networks in particular for e-scooter usage records presents a resounding example of technological innovation using operational performance. The fundamental issue in this discipline is precisely predicting call for styles that is a tough assignment due to the fact user behavior is dynamic and there are different variables that have an effect on it which include the climate, visitors and urban infrastructure. Confronted with this issue the GA-LSTM model plays quite properly in as it should be forecasting the demand for e-scooters. The GA aspect is essential for improving the hyperparameters of the LSTM community, which allows it to be tuned. This change is crucial since it significantly improves the LSTM capability to perceive the non-linear styles and temporal relationships gift inside the e-scooter usage information. With a view to allocate sources successfully within the shared economy an intensive and specified knowledge of call for traits is ensured by the GA-LSTM model. As a result, there are fewer times of oversupply or scarcity of e-scooters at some stage in various urban locations increasing utilization whilst lowering operating charges. The GA-LSTM version is a robust tool for long-term software because of its adaptability to converting situations and ability to examine from sparkling data. The version can continuously adapt to new styles as the shared financial system landscape modifications preserving its excessive accuracy over the years. For e-scooter groups operating in dynamic metropolitan contexts wherein purchaser alternatives and outside factors might change speedy this capability is particularly beneficial. There are numerous realistic blessings of making use of the GA-LSTM model in the shared financial system. With the aid of guaranteeing the provision of e-scooters while and while they may be wished it improves patron happiness. It results into decrease overhead, advanced fleet control and operational efficiencies for service carriers. Additionally, the version facilitates acquire city sustainability dreams with the aid of minimizing the environmental effect of transportation offerings and maximizing the use of shared sources by using permitting extra accurate call for prediction. For this reason, the GA-LSTM version is a specifically powerful manner to capitalize on the opportunities of facts-pushed selection-making inside the shared economic system.

Step 1: Initialize the generation count $n = 0$
Step 2: While $n < 50$:
Step 3: Generate a stochastic pool populace of chromosomes representing ability LSTM configuration with various hyperparameters including quantity of layers, neurons consistent with layers gaining knowledge of prices.
Step 4: Evaluate each chromosome using the fitness function relevant to e-scooter usage prediction, typically based on prediction accuracy or error rates on a validation dataset.
Step 5: Select a certain number of the fittest chromosomes based on their fitness scores. These selected chromosomes form the initial population for the next steps.
Step 6: Pair chromosomes for mating using a crossover operator. This process involves combining parts of two parent chromosomes to create offspring, promoting genetic diversity.
Step 7: Apply Crossover to the selected pair at randomly chosen points (with a crossover probability, GAPrc = 0.8) determining how often crossover occurs.
Step 8: Mutate the offspring generated from the Crossover operation (with a mutation probability, GAPrum = 0.001). Mutation involves randomly altering certain genes in the chromosome. Set a mutation probability to control the mutual rate.
Step 9: Form the new population from the offspring, ensure that it adheres to size constraints and prioritize the most fit chromosomes.
Step 10: Replace the old population with the new one and increment the generation count n *by* 1.
Step 11: After the final generation select the optimal chromosomes based on the highest fitness score. This chromosome represents the best LSTM configuration for predicting E-scooter usage.
Step 12: Apply this optimal LSTM configuration to build and train the final model for E-scooter usage prediction.

The generation count n is initialized to zero at the start of this operation. The technique iteratively refines the LSTM model configuration for a maximum of 50. The GA to start with creates a numerous pool of chromosomes in each era. A possible LSTM configuration is represented by means of each chromosome, which is defined by using a diffusion of hyperparameters, inclusive of the variety of layers, the variety of neurons in step with layer, and the studying price. This stochastic pool is crucial for investigating a diffusion of possible fixes. Subsequently, a health feature is used to assess every chromosome's effectiveness. The use of a validation dataset is mainly connected to the utilization patterns of e-scooters; this feature commonly evaluates the prediction accuracy or blunders costs of the LSTM setup. A variety of the most promising chromosomes is made primarily based on their health rankings. The starting population for the following evolutionary ranges is made up of these selected chromosomes. Chromosomes are paired for mating in the evolutionary system by means of a crossover operator. By way of developing youngsters by combining components of figure chromosomes, this operator provides genetic variety to the populace. The crossover is performed at arbitrary locations alongside the chromosomal strings, and the frequency of this blending is determined with the aid of a predetermined chance. The subsequent essential stage is mutation, in which the progeny produced by means of crossover revel in haphazard changes in certain genes. This mutation adds a greater range and facilitates the algorithm's exploration of a bigger answer space. It is regulated by means of a predetermined opportunity. The progeny provides rise to a new population following crossover and mutation. To be able to maintain size restrictions and provide precedence to the fittest chromosomes, this populace is carefully selected to ensure that the maximum viable options are pursued. The set of rules constantly replaces the older and much less evolved populace with the brand new, greater, superior populace because of the generations. The set of rules chooses the pleasant chromosome based on the best health rating as soon as it reaches the final technology. The correct chromosome for exactly forecasting e-scooter utilization is represented by this LSTM setup. In the long run, the LSTM version is built and educated on the usage of this best configuration, after which it's far implemented to the practical intention of forecasting e-scooters call for. With its progressed prediction accuracy guaranteed by means of this GA-optimized LSTM version, it is a useful tool for effectively organizing and overseeing e-scooter fleets in city settings.

Algorithm 1 LSTM Cell for E-Scooter Usage Prediction

Input: E: Sequence of input E-scooter usage, where $x = \{x_1, x_2, \ldots, x_t\}$, H_{t-1}-previous hidden state, C_{t-1}-Previous Cell state, Weight matrices $W_{Fo}, W_{In}, W_{Ou},\ W_c$; Bias Terms-$B_{Fo}, B_{In},\ B_{Ou},\ B_c$.
Output: h_t-current hidden state, c_t- current cell state
Initialization:
Initialize h_o, c_o as the preliminary hidden and cell states.
Outline weight matrices $W_{Fo}, W_{In}, W_{Ou},\ W_c$ for forget gate, input gate, output gate and cell state respectively.
Outline Bias term $B_{Fo}, B_{In},\ B_{Ou},\ B_c$ corresponding to each gate.
for each time step t **do**
    calculate forget gate $Fo_t = \sigma(W.\,[h_{t-1}, x_t] + B_{Fo})$
    Calculate the input gate $In_t = \sigma(W_{In}.\,[h_{t-1}, x_t] + B_{In})$
    Calculate Candidate cell state $\overline{c_t} = \tanh(W_c.[h_{t-1}, x_t] + B_C)$
    Update cell state $c_t = Fo_t * c_t - 1 + i_t * \overline{c_t}$
    Calculate output gate $Ou_t = \sigma(W_{Ou}.[h_{t-1}, x_t] + B_{Ou})$
    Calculate hidden state $h_t = Ou_t * \tanh(c_t)$
    Output the hidden state h_t and cell state c_t at each time step t
end for

3.2.2. LSTM. Initializing the preliminary states is step one in the process. The hidden and cell states are among these early levels, and they may be important for encapsulating the temporal dependencies within the facts. Later, the version specifies wonderful weight matrices and bias terms for diverse LSTM components. The overlook gate, input gate, output gate, and mobile kingdom are a number of those elements. Every such a is vital to the manner the LSTM interprets and keeps information through the years. The LSTM model executes a number of computations as it examines the input statistics bearing on e-scooter usage at every time step. It starts by means of ascertaining the output of the forget gate which determines what statistics is removed from the cell state. The quantity of latest information that enters the cell state is then managed through calculating the output of the input gate. Similarly, a candidate cellstate is produced, supplying the cell state a probable new cost. The version then combines the new candidate state with the old state to update the real cell state. This up-to-datecell state is essential since it contains information this is used during the sequence's processing. The output of the output gate is computed as soon as the cell state is up to date. Using the updated cellstate as a basis, this output gate determines the following concealed state. The ultimate stage within the manner is to compute the current hidden state, which stores the expertise that the LSTM has learnt up to that factor in time. After that, the hidden state is probably processed similarly or used to make predictions before shifting on to the next time step. So as to boom the prediction accuracy of the LSTM model, the GA adjusts its parameters at some point of this procedure. The model is specifically beneficial for forecasting e-scooter demand and utilization tendencies in this optimization, which makes it a priceless tool for handling e-scooter fleets and making operational choices within the shared financial system enterprise.

4. Results and Experiments.

4.1. Simulation Setup. The dataset which is used to assess the proposed of the look at based on shared e-scooters and is used to broaden a version for predicting demand which is customized from the study [12]. It consists of comprehensive ride records from a selected e-scooter carrier, protecting numerous elements which

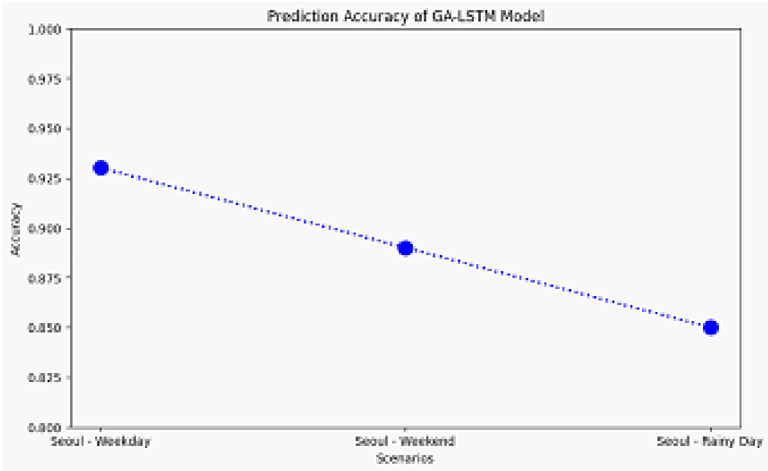

Fig. 4.1: Prediction Accuracy

includes condominium dates and times, places, journey periods, and distances. The temporal scope of the facts is about for a particular month, and the spatial scope covers two widespread areas in Seoul, Korea. The facts is based into a grid device for efficient evaluation, with every grid representing a specific area. This established method allows for distinctive insights into e-scooter usage patterns, which is vital for predicting call for appropriately.

4.2. Evaluation Criteria. The accuracy of the suggested GA-LSTM model, as shown in the figure 4.1 suggests the efficacy in the usage of e-scooters in more than a few actual-international situations. The version extremely good accuracy of 0.93 inside the Seoul Weekday state of affairs shows that it's miles particularly correct at predicting the call for for e-scooters on normal workdays. Due to its excessive precision, the version can be capable of capture and examine e-scooter utilization styles in an average city setting during the operating day, which is a vital functionality for fleet control and aid allocation. To 0.89 inside the Seoul Weekend scenario the accuracy declined. This is a respectably high diploma of accuracy, although it is a tiny drop from the weekday scenario. This suggests that the GA-LSTM version skillfully adjusts to the diverse utilization patterns which can be generally found all through weekends. This variance may additionally end result from variations in person behavior and e-scooter utilization patterns on weekends as evaluation to weekdays, which the version largely displays. Moreover, the accuracy of the version become zero.Eighty five in the more hard Seoul wet Day situation. Regardless of the decline, this wide variety is spectacular, specially in mild of the fact that certain climate situations, which includes rain, can appreciably alternate e-scooter usage patterns. Its potential to interpret and assume intake information accurately even in less-than-perfect situations is tested by the GA-LSTM model's robustness, as proven by means of this degree of accuracy underneath such situations. Normal, these accuracy numbers exhibit how well the GA-LSTM version performs in predicting e-scooter utilization in an expansion of settings. Its capability to stay very correct in a spread of settings, such as weekends, ordinary weekdays, and extreme weather, indicates that it is able to prove to be a useful tool for groups that offer shared e-scooter services, assisting each operational effectiveness and strategic selection-making.

LSTM networks are adept at handling sequential data, capturing long-term dependencies that are often present in time-series data. The GA's optimization process further enhances the LSTM's ability to model complex patterns in the data, leading to superior prediction accuracy compared to traditional models or non-optimized neural networks.

Figure 4.2 presents the efficacy of GA-LSTM version in phrases of mean Squared error (MSE) throughout more than one possibilities offering treasured insights into the version precision. The MSE of.05 became found by means of the version in the Seoul Weekday situation. This low MSE score indicates that the GA-LSTM version projections at some stage in common workday conditions are fantastically accurate with the predictions

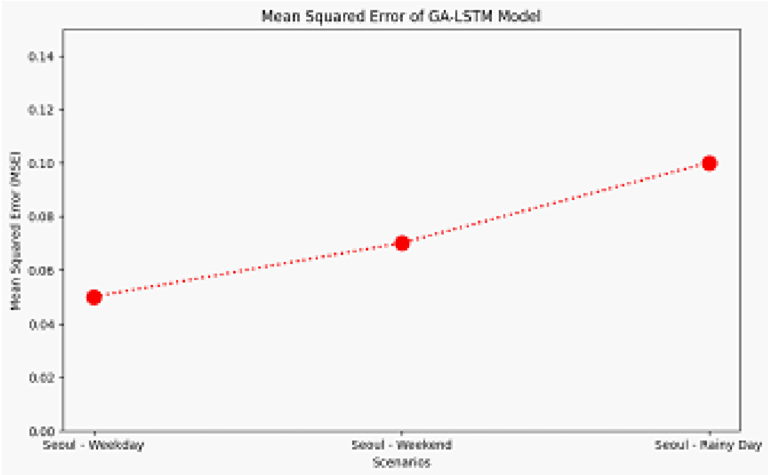

Fig. 4.2: MSE

coming in fairly near to the actual e-scooter utilization information. Planning and resource allocation in e-scooter sharing offerings rely heavily on this level of precision, specifically when estimating demand on ordinary workdays whilst utilization styles may be steadier and greater predictable. While we switched to the Seoul Weekend situation the MSE went up a notch to 0.7. Even while this shows a minor discount in the version's accuracy compared to the weekday situation, it is nonetheless quite correct. Because of varying user conduct, which include tour or entertainment activities, weekends normally show numerous usage patterns, that may upload similarly variability to the data. In spite of these problems, the GA-LSTM version retains a relatively low MSE, highlighting its potential to modify to quite a number utilization scenarios. The MSE to 0 to1 within the greater tough Seoul wet Day state of affairs. Rain and other damaging climate styles may have a large influence on e-scooter usage, which will increase the data's unpredictability and variability. The model maintains to characteristic very efficaciously regardless of this growth in MSE, demonstrating its resilience and potential to manage versions in intake patterns introduced on by means of out of doors variables like climate shifts. All things taken into consideration, the MSE values in each of those conditions reveal how correct and dependable the model is at predicting the demand for e-scooters. The efficacy of the GA-LSTM version as a beneficial tool for e-scooter sharing services is tested by way of its capability to provide correct forecasts beneath an expansion of eventualities, which facilitates with operational planning and green useful resource control.

The processing time values of figure 4.3 provides the efficacy of the cautioned GA-LSTM. The version validated a processing time of 20 seconds within the Seoul Weekday situation which is a really fast reaction time this is very wonderful for dynamic e-scooter sharing operations. Rapid processing velocity guarantees that e-scooter service providers can act speedy based on version predictions, that's important for weekday operations wherein responsiveness and brief turnaround are critical. Whilst we switched to the Seoul Weekend scenario the processing time elevated by using a small amount to 25 seconds. Even though there may be a moderate growth over the weekday scenario, it's miles nonetheless within a variety that can be utilized in real time with achievement. The technique continues a reasonably rapid processing time on weekends, whilst e-scooter utilization patterns may range due to rest sports or an growth in tourists. This ensures that provider providers can speedy regulate to the changing needs. The processing time was extended to 30 seconds within the Seoul wet Day scenario. This scenario has the longest duration of all 3 but it's miles nonetheless affordable for operational application. Random changes in consumer behavior because of adverse weather conditions consisting of rain, might complicate the prediction version and boom the processing time required for effective forecasting. Even in much less-than-best climate, the version's processing time is still powerful sufficient to permit the timely deployment and manipulate of e-scooter fleets. Standard, the processing time values within

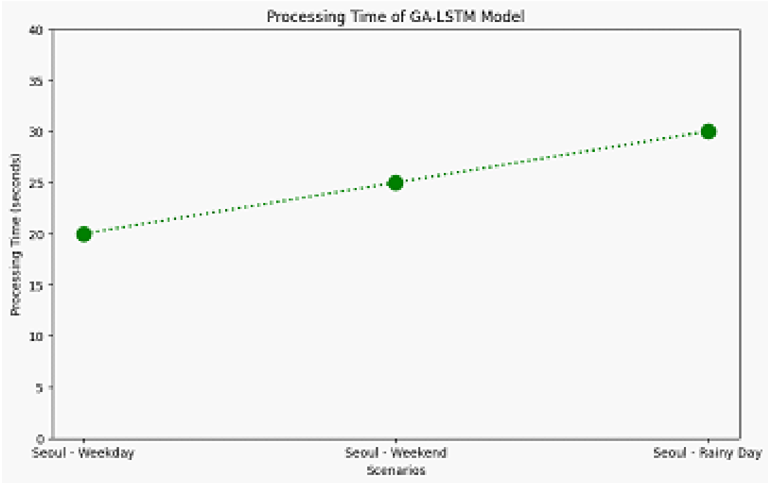

Fig. 4.3: Processing Time

the numerous situations display that the GA-LSTM model produces straightforward and accurate predictions however additionally does so in a timely way that allows choice-making in real time. The GA-LSTM model is a beneficial tool in the rapid-paced world of e-scooter sharing offerings due to its performance in processing time which permits operators to efficiently optimize their services and react fast to converting call for.

By reducing the requirement for manual intervention throughout the model development process, GA for hyperparameter tweaking helps to save time and money. This automated method of optimizing models can be very helpful in quickly changing domains where efficiency and time-to-market are crucial.

5. Conclusion. The take a look at locating on the GA-LSTM approch capacity to predict e-scooter usage in the shared economy region is encouraging and factors to vital developments inside the area of predictive analytics. The version efficiently combines the advantages of LSTM networks and GA to provide a powerful tool that can expect e-scooter demand with accuracy in an expansion of scenarios. As may be seen from the prediction accuracy determine which suggests how nicely the version predicts intake patterns on weekdays, weekends or even in hard conditions like rainy days, the have a look at indicates that the model achieves excellent accuracy. For the version to be used practically in maximizing the distribution and availability of e-scooters, this precision is essential. Furthermore, the accuracy of the model is demonstrated via the MSE values which spotlight its capability to exactly in shape its predictions with actual usage facts even in the face of the intricacies and variability of user behavior. This degree of accuracy demonstrates the GA-LSTM version resilience, making it a truthful aid for provider providers. Particularly the version processing instances additionally show how effective it's far. Regardless of the complexity of the analysis and prediction of e-scooter usage, the model can manage information quick, that's essential for real-time applications inside the shared financial system industry. This efficacy boosts operational effectiveness and customer delight by way of allowing e-scooter service vendors to make set off, properly-knowledgeable decisions. In conclusion, the GA-LSTM model is a huge breakthrough for system getting to know packages in sharing economic system offerings. Its capability to deliver particular, well timed, and accurate predictions can drastically help e-scooter provider vendors optimize their operations, efficiently manipulate their sources, and in the long run help the growth and sustainability of the shared economic system surroundings. The examine now not handiest confirms the effectiveness of the GA-LSTM version but additionally gives possibilities for continued studies and development on this vicinity, that may in the end result in the creation of extra complex and superior forecasting gear.

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Edited by: Sathishkumar V E
Special issue on: Deep Adaptive Robotic Vision and Machine Intelligence for Next-Generation Automation
Received: Feb 5, 2024
Accepted: Apr 4, 2024