Multi-Level Attention Networks for Multi-Step Citywide Passenger Demands Prediction

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Abstract - This study presents a unique method that combines Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Naive Bayes (NB) to improve the effectiveness of airport passenger bus scheduling. Flight schedules and passenger traffic historical data are carefully gathered, pre-processed, and important attributes are extracted for input. The ANN is used to capture complex, nonlinear interactions that are present in the data, while SVM and NB are used for classification tasks linked to identifying when bus services are required. A thorough evaluation of the model's performance is conducted using measures like accuracy and precision. Through the use of a weighted method, the outputs of the three models are smoothly blended. The contribution of each model is weighted according to its past performance or unique features. When implemented in an actual airport setting, the resultant system provides a productive and adaptable means of scheduling passenger buses. Regular updates to the model, informed by fresh data, guarantee continuous progress and allow the system to adjust to changing needs and trends. In order to optimize airport transportation logistics and provide the groundwork for improved operational effectiveness and customer pleasure, this hybrid system is presented as a viable and workable solution.
Keywords: Multi-Step Demands Prediction, Convolutional Neural Network, LSTM, Multi-Level Attention

1.INTRODUCTION

Within the field of urban transportation forecasting, the precise estimation of passenger needs over the whole city is essential for transportation system optimization and overall efficiency improvement. Multi-Level Attention Networks (MLANs) emerge as a sophisticated solution for Multi-Step Citywide Passenger Demands Prediction (MSCPDP), recognizing the complex and dynamic character of urban transportation patterns. It not only takes into account the temporal and spatial complexity present in urban environments, but it also makes it easier to predict future passenger demands at different time intervals.

1.1 MULTI STEP DEMANDS PREDICTION

Anticipating multi-step passenger needs is a crucial task for effective urban mobility planning in the field of transportation forecasting. The dynamic and changing patterns of transportation demands in metropolitan areas make it difficult for standard models to provide precise and detailed forecasts over long periods of time. Multi-step demands prediction is a job that entails predicting passenger wants for future time intervals as well as the near future while taking into account the complex interactions between different components. This calls for sophisticated prediction models that can identify long-term trends as well as short-term changes. Novel techniques seek to improve the accuracy and consistency of passenger demand forecasts by tackling the problems with this multi-step forecasting paradigm. This will help to improve urban transportation planning and management.

1.2 CNNs

CNNs are potent and revolutionary family of algorithms in the field of artificial intelligence and machine learning, especially in the field of computer vision. CNNs, which are intended to replicate the visual processing powers of the human brain, have shown remarkable efficacy in tasks including object identification, feature extraction, and picture recognition. Convolutional layers, which apply filters to input data in a methodical manner and allow the network to automatically acquire hierarchical feature representations, are the architectural hallmark of CNNs. CNNs are well-suited for tasks requiring complicated visual information because of their distinctive architecture, which enables them to capture spatial hierarchies and patterns within data. CNNs are very versatile and can be used not only image analysis but also in a wide range of domains,. This flexibility highlights their importance in pushing the boundaries of deep learning and pattern recognition.

1.3 LSTM

Long Short-Term Memory (LSTM) networks, are significant development in the area of Recurrent Neural Networks (RNN). They were created with the express purpose of resolving the difficulties associated with identifying and maintaining temporal connections in sequential data. Since LSTMs have a distinct architecture with memory cells and gating mechanisms, These networks are especially good at simulating long-range relationships. This makes them ideal for applications like Sequential Pattern Recognition, Natural Language Processing, and Time Series Forecating. LSTMs provide enhanced learning and retention of information over longer sequences by addressing the disappearing and expanding gradient issues that conventional RNNs face. This makes them an essential component of many applications where comprehending and using temporal context is critical to obtain precise and contextually aware predictions, greatly enhancing the effectiveness of deep learning in sequential data processing.

1.4 MULTI-LEVEL ATTENTION

In the field of deep learning, Multi-Level Attention (MLA) is a novel paradigm that tackles the challenging problem of processing input across hierarchical structures. MLA attention is a sophisticated method of collecting complex interactions and dependencies within data at distinct abstraction levels. It is an extension of attention processes. By using this technique, neural networks may be trained to preferentially concentrate on characteristics that are important across different hierarchical levels, which improves the model's ability to understand and interpret complicated patterns. When used in a variety of fields, including CV, NLP and TSF, MLA attention networks have shown to be very effective in processing complex representations of information. This introduction lays the groundwork for investigating how multi-level attention may be used as an effective tool to enhance the interpretability and performance of deep learning models in a variety of applications.

2. LITERATURE SURVEY

In this study, Luis Moreira-Matias[1] et al. have suggested an increasingly important component of boosting the viability of taxi businesses is informed driving. Every car has sensors installed, which open up new possibilities for autonomously acquiring knowledge and delivering data for in-the-moment decision making. Many sensory data sets are already being explored by intelligent transportation systems for time-saving route finding and taxi dispatching. This research presents a unique approach that uses streaming data to estimate the geographical distribution of taxi passengers over a short time horizon. The data was first combined into a time series histogram. The prediction was then created by combining three time-series forecasting methods. Using online data supplied by 441 fleet cars operating in Porto, Portugal, experimental experiments were carried out. The findings showed that, given a 30-min horizon, the suggested approach may provide useful insight into the spatio-temporal distribution of taxi-passenger demand. Global Positioning System (GPS), Global System for Mobile Communications (GSM), and WiFi are examples of advances in sensor and wireless communications that have made it possible to communicate with moving vehicles and get pertinent data about their position and condition. These types of technology are now found in the majority of taxis, creating a new source of rich spatiotemporal data. Such data and/or interfaces are already being effectively explored by intelligent transportation systems for effective taxi dispatching, time-saving route finding, fuel-saving routing, and taxi pooling. Both drivers and taxi businesses are seeing a decline in earnings due to the growing cost of gasoline. As a result, there is an imbalance between the number of cabs operating and the demand from passengers, which lowers both the businesses' earnings and customer satisfaction levels .

In this study, Han-wen Chang[2] et al. have argued that: In an urban region, the supply and demand of taxis are not necessarily equal. In order to forecast demand distributions in relation to time, weather, and taxi location settings, this research suggests mining historical data. Data filtering, clustering, semantic annotation , and hotness computation are the four steps in the procedure. An online mash-up application comparing and showcasing the outcomes of three clustering algorithms demonstrates how context-aware demand prediction may enhance taxi fleet management.

In this work, Yexin Li[3] et al. have suggested that in many large cities, bike-sharing programs are extensively implemented, offering residents a handy way to get about on their commutes. The bikes in a system need to be rebalanced often because the rentals and returns of bikes at various stations at different times are out of balance. Since it takes too long to reallocate the bikes once an imbalance has formed, real-time monitoring is unable to effectively address this issue. In order to facilitate reallocation, this study provides a hierarchical prediction model to forecast the quantity of bikes that will be rented from or returned to each station cluster in the future. In order to create a two-level hierarchy of bike stations, the model suggest a bipartite clustering technique for grouping bike stations together. A Gradient Boosting Regression Tree (GBRT) predicts how many bikes will be rented out in total in a city. The number of bikes that are rented out and returned to each cluster may therefore be simply estimated using a multi-similarity-based inference model that is presented to forecast the rent percentage across clusters and the inter-cluster transition. The model was tested using two bike sharing programs, one in Washington, D.C., and the other in New York City (NYC). The results validate the benefit of the model over baseline techniques (0.03 reduction of mistake rate), particularly during anomalous times (0.18/0.23 reduction of error rate).In several large cities, like Beijing, Paris, and New York, bike-sharing programs are extensively implemented and provide a practical means of transportation for daily commutes. A bike may be rented (checked out) from a station close to the user's origin and returned (checked in) to a station near the user's destination. Swiping an RFID card is necessary for users to check in and out of bikes. including every card swipe, a record is created including the bike ID, timestamp, and station ID. Bike rebalancing between stations is an issue for bike-sharing systems. Bicycle utilization is inherently biased and varies with time and place. As such, some stations could be overcrowded and run out of docks for future returned bikes, while others might not have any bikes accessible for interested riders. The problem cannot be fully addressed by counting the number of bikes at each station right now since it is too late to reallocate bikes after an imbalance has formed.

In this research, Longbiao Chen[4] et al. have suggested The usage of bike sharing as an environmentally friendly form of transportation is growing around the world, however frequent overcrowding at stations devoid of bikes or docks negatively impacts users' experiences. Given how dynamic and context-dependent a station's bike use behavior is, it is challenging to forecast which specific over-demand stations may need preventative action. Furthermore, a significant difficulty is that the way that bike use patterns are influenced by both oppo` local officials to guarantee the complete functionality of the bike sharing system, considering the substantial expenditures associated with establishing bike stations and updating bike lanes. Preventing stations from over-demanding, or from being entirely empty or filled for a lengthy amount of time, is one of the main criteria. If a user encounters an over-demand station, their experience might be significantly hampered since they would have to locate another station where the bike is available for hire or return, which could eventually prevent users from using the bike sharing system. Consequently, local government representatives often request that operators of bike sharing programs address and avoid this over-demand issue by, for instance, imposing penalties when it arises. In light of the many and very dynamic circumstances, we provide in this research a dynamic cluster-based methodology to forecast the occurrence of over-demand in bike sharing systems.

In this article, Junbo Zhang [5] et al. have suggested Thanks to developments in wireless communication and location-acquisition technology, spatiotemporal (ST) data—which has distinct temporal and spatial qualities including proximity, period, and trend—is now more widely available. They provide a deep learning-based prediction model for spatiotemporal data (DeepST) in this study. They use our expertise in the ST sector to create the two parts of Deep ST's architecture: the spatio-temporal and the global. The spatio-temporal component models temporal proximity, period, and trend in addition to spatial near and distant relationships concurrently using the framework of convolutional neural networks. Day of the week, workday, and weekend are examples of global elements that are captured by the global component. They develop UrbanFlow1, a real-time crowd flow forecasting system, using DeepST. The results of experiments conducted on a variety of ST datasets confirm that DeepST can accurately capture the spatiotemporal features of ST data, demonstrating its benefits over the four baseline approaches. Massive volumes of data with spatial coordinates and timestamps, known as ST data, are the result of advances in location-acquisition and wireless communication technologies. These domains include environmental science, transportation, communication systems, social networking services, and communication systems. ST data differs from text and picture data in that it includes two distinct characteristics: temporal qualities, which include proximity, period, and trend; and spatial features, which include a geographical hierarchy and distance. In this research, They developed a simultaneous temporal and spatial property-capturing DNN-based prediction model for ST data. They use it in the development of Urban Flow, a real-time crowd flow forecasting system that assists users in tracking historical crowd movements and projecting future ones. They test DeepST on many ST prediction tasks, such as traffic flows, crowd flows, and bike rental/return tasks, and find that its performance surpasses the four baselines.

3. EXISTING SYSTEM

Predicting passenger requests based on past mobility journeys is crucial for the new mobility-on-demand services in order to improve vehicle allocation. Previous research has concentrated on forecasting passenger demand at certain places, or hotspots, for the next stage. Nevertheless, They contend that multi-step citywide passenger demands are more advantageous for preventing demand-service mismatching and creating efficient vehicle distribution/scheduling plans as they capture both time-varying demand trends and worldwide statuses.

Moreover, they discover that single-step technique modifications cannot provide strong predictions with high accuracy for subsequent phases. They provide an end-to-end deep neural network model for the prediction problem in this research. In order to discover complex characteristics that represent spatiotemporal impact and pickup-drop off interactions on citywide passenger needs, They use an encoder-decoder system based on convolutional and Conv LSTM units. To capture crucial temporal dependencies and highlight the consequences of latent citywide movement regularities, They offer a multi-level attention model (global attention and temporal attention). They test their proposed technique on real-world mobility excursions (bikes and taxis), and the experimental findings demonstrate that our method outperforms the state-of-the-art methods in terms of prediction accuracy.

4. PROPOSED SYSTEM

This study uses a hybrid technique that combines ANN SVM and NB to improve airport passenger bus scheduling. Flight schedules and passenger traffic from the past are gathered, preprocessed, and pertinent characteristics are retrieved for input. While SVM and NB are used for classification tasks relating to the requirement for bus services at specified times, an ANN is used to capture complicated, non-linear interactions. The accuracy and precision of the models are measured, and a weighted technique is used to combine the three models' results. When the final system is implemented in a real-world setting, it offers a dynamic and effective way to schedule passenger buses at airports. Regular model updates based on fresh data enable the system to continuously improve.

5. MODULES DESCRIPTION

5.1 LOAD AIRPORT PASSENGERS ARRIVAL DATASET

The dataset providing details on passenger arrivals at the airport must be loaded by this module. Features like arrival timings, flight information, and passenger numbers are probably included in the dataset. An essential first step in any further research and modeling pertaining to airport passenger arrivals is loading this information.

5.2 LOAD BUS DATASET

The purpose of this module is to import a different dataset containing data pertaining to buses. Details like bus routes, timetables, and passenger numbers could be included. In order to combine bus-related data with passenger arrival data at airports and conduct a thorough analysis for the purpose of improving airport bus scheduling, loading this dataset is necessary.

5.3 AIRPORT BUS SCHEDULING USING ANN, SVM, AND NB

In order to enhance bus scheduling at the airport, this module focuses on using machine learning methods, including ANN, SVM, and NB. Several features of the transportation system, including patterns of passenger demand, the best times to schedule appointments, and effective routes, are modeled and predicted by these algorithms. A comparative study is made possible by the employment of numerous algorithms, guaranteeing flexible and resilient scheduling techniques that may take into account various features of the airport environment.

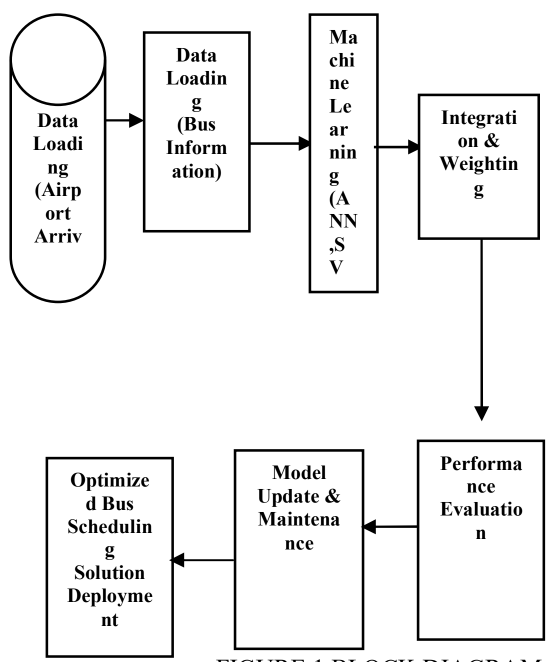

FIGURE 1 BLOCK DIAGRAM

5.4 ALGORITHM DETAILS

A well-liked supervised machine learning model for categorization and prediction of unknown data is called SVM. Many academics claim that SVM is a very accurate text categorization method. It is also often used to the categorization of emotion. For example, we may train a model to categorize incoming data into the positive and negative review categories if we have a dataset with data already pre-labeled into these two groups. This is the precise operation of SVM. In order for the model to assess and categorize unknown data into the categories that were present in the training set, we train it on a dataset. SVM is a technique for linear learning. It determines the best hyper-plane to distinguish between two classes. As a supervised classification model, it seeks to improve classification performance on test data by maximizing the distance between the nearest training point and either class.

Table 1.COMPARISON TABLE

```
from sklearn.svm import SVC
# Instantiate SVM classifier
svm_model = SVC(kernel='linear', C=1.0)
# Train the model
svm_model.fit (X_train, y_train)
# Make predictions
svm_predictions = svm_model.predict(X_test)
```

A straightforward probabilistic method used in classification, the NB algorithm determines its probability value by calculating value and frequency combinations from the related collection. All characteristics are assumed to be independent by this method. Several hints or instructions are required by the NB classification process in order to identify the class of the data that has to be examined.

```
from sklearn.naive_bayes import GaussianNB
# Instantiate Naive Bayes classifier
nb_model = GaussianNB()
# Train the model
nb_model. Fit(X_train, y_train)
# Make predictions
nb_predictions = nb_model.predict(X_test)
```

A family of machine learning models called ANN is motivated by the composition and operations of the human brain. An input layer, one or more hidden layers, and an output layer are the three layers made up of linked nodes that make up an ANN. In order to produce accurate predictions, the network learns to modify the weights assigned to each link between nodes during training.

```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
# Build ANN model
ann_model = Sequential()
ann_model.add(Dense(units=128, activation='relu', input_dim=input_dim))
ann_model.add(Dense(units=1, activation='sigmoid'))
# Compile the model
ann_model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
# Train the model
ann_model.fit(X_train, y_train, epochs=10, batch_size=32)# Make predictions=ann_predictions =
ann_model.predict (X_test)
```

5. RESULT ANALYSIS

A thorough analysis was conducted on the outcomes of the suggested hybrid technique, which included ANN, SVM, and NB to optimize airport passenger bus scheduling. Performance measures including precision and accuracy were used to assess how well the integrated models worked. An effective scheduling method that took into account several features of the airport environment was made possible by the weighted combination of the outputs from ANN, SVM, and NB. When the system was implemented in a real-world environment, it demonstrated its effectiveness and flexibility and offered an ideal bus scheduling solution. Frequent updates based on fresh data guaranteed ongoing development, allowing the system to adapt quickly to shifting passenger.

ALGORITHM	ACCURACY	PRECISION	RECALL	F1-SCORE
ANN	91.39	85.94	88.55	87.22
SVM	93.51	85.79	89.85	87.77
NB	94.48	86.74	90.53	88.59

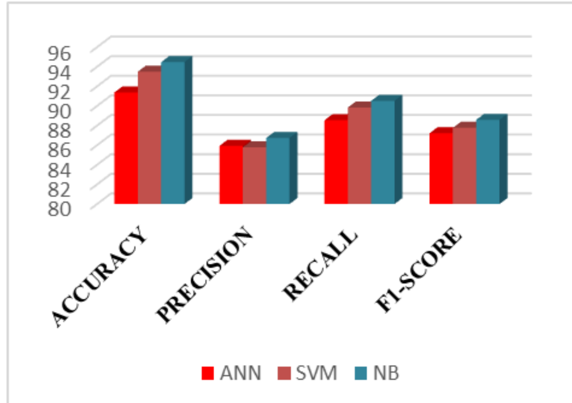

Table 2COMPARISON GRAPH

6. CONCLUSION

To sum up, the creation and use of the airport bus scheduling system constitute an all-encompassing, data-driven strategy for improving transportation management in airport settings. The system has undergone thorough testing, machine learning model integration, and meticulous design, and it is now ready to deliver optimum bus timetables based on intricate relationships between passenger arrivals and bus operations. The effective use of this approach improves overall operational efficiency in addition to streamlining airport bus services. A dynamic and flexible framework is provided by the integration of sophisticated algorithmic inputs to handle the constantly evolving needs of airport transportation. This system is a proactive answer to the issues of optimizing bus services in a busy airport environment. As airports continue to expand, adding intelligent scheduling solutions becomes more vital. The system's durability and effectiveness in satisfying the changing demands of airport logistics and passenger services are guaranteed by the ongoing monitoring and improvement techniques included into the implementation.

7. FUTURE WORK

Future development presents a viable path for the airport bus scheduling system to advance and adapt to new difficulties. Enhancing the system's responsiveness and forecast accuracy might include adding real-time external data like weather, travel delays, and special events. Furthermore, investigating the incorporation of more sophisticated machine learning methods, such as reinforcement learning, may enable the system to gradually learn and improve its scheduling algorithms. Additional cooperation with stakeholders, such as transportation and airport authorities, may help to improve the system by providing real-world knowledge and user input. The use of cutting-edge data sources, such sensor networks and Internet of Things devices, may provide richer datasets for more sophisticated decision-making as technology develops. The ultimate goal of future development should be to further enhance the adaptability, resilience, and alignment of the airport bus scheduling system with the changing requirements of passenger services and airport logistics.

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