Prediction of Passenger Flow In Public Transportation

Mr. Moorthy.K[1], Padma Sowgandhika.M[2], Praveen.S[3], Siva Prakash.S[4]
[1]Assistant Professor, Dept of CSE
[2, 3, 4]Dept of CSE
[1, 2, 3, 4] Sri Ramakrishna Institute of Technology

Abstract- *Predicting passenger flow in public railway transportation is a complex task that involves analysing various factors, such as the time of day, the day of the week, and the season, as well as special events and holidays that may affect travel patterns. Machine learning algorithms can be used to analyse this data and develop accurate predictions of passenger flow. By continuously collecting and analysing data, these models can be updated in real-time, allowing transportation operators to make more informed decisions about scheduling and resource allocation.*

Other factors that may impact passenger flow predictions include changes in weather, unexpected events such as accidents or disruptions, and changes in public health policies or transportation regulations. To account for these factors, it may be necessary to incorporate real-time data feeds into the predictive model, allowing it to adjust and adapt as new information becomes available.

Keywords- Comma–Separated Values, Hue Separation Value, Long Short-Term Memory, Recurrent Neural Network, Integrated Development Environment, Support Vector Machines, Convolutional Neural Network.

I. INTRODUCTION

There are several reasons that can lead to overcrowding in railway stations, Limited capacity: Railway stations have a limited capacity in terms of the number of people they can handle at a given time. When the number of people exceeds the capacity, it can lead to overcrowding.Rush hour: During peak hours, such as early morning and evening rush hours, more people tend to travel by train, leading to overcrowding in railway stations.Delayed trains: When trains are delayed or cancelled, it can cause a backlog of passengers waiting for the next train, leading to overcrowding in the station.Special events: During special events, such as concerts, sporting events or festivals, large numbers of people may travel to and from the station, leading to overcrowding.Insufficient infrastructure: In some cases, railway stations may not have adequate infrastructure to handle the volume of passengers, such as lack of seating, inadequate number of platforms, or insufficient ventilation. Lack of crowd management: Sometimes, railway stations may lack proper crowd management techniques, leading to chaotic situations and overcrowding.It is important for railway authorities to address these issues to ensure the safety and comfort of passengers.

II. LITERATURE SURVEY

1)JIANYUAN GUO, ZHEN XIE, YONG QIN , LIMIN JIA , AND YAGUAN WANG [2019]

They proposed a model based on the fusion of support vector regression (SVR) and long short-term memory (LSTM) neural network is proposed. The inputs of the model are the abnormal features, which consist of the recent real volume series and the predicted volume series based on the periodic features. A two-stage training method is designed to train the LSTM model, which can reflect the large fluctuations of abnormal flow more timely and approximately. A combination method based on the real-time prediction errors is proposed, on which the outputs of SVR and LSTM are combined into the final outputs of the prediction model. The results of the experiments show that the SVR-LSTM model more accurately reflects the abnormal fluctuations of passenger flow, which performs well and yields greater forecast accuracy than the individual models.

2) Yifan Tan, Haixu Liu, Yun Pu, Xuemei Wu and Yubo Jiao, "Passenger flow prediction of integrated passenger terminal based on K-Means-GRNN" [2021]

This paper proposed the passenger flow GRNN prediction model based on the K-means cluster algorithm, and an improved index named Between-Within 17 Proportion-Similarity is proposed to improve the clustering effect of K-means so that the clustering effect of the new index is verified. In addition, the passenger flow data are studied and trained by combining with the GRNN neural network model based on parameter optimization; the passenger flow prediction model is obtained. Finally, the passenger flow of Chengdu East Railway Station has been taken as an example, which is divided into 16 models, and each type of passenger flow is predicted, respectively. Compared with the traditional method, the results show that the model can predict the passenger flow with high accuracy.

3)Wei Li, Liying Sui, Min Zhou &Hairong Dong, "Short term passenger flow forecast for urban rail transit based on multi source data" [2021]

They proposed a model that can adapt to the complexity, nonlinearity, and periodicity of passenger flow in urban rail transit. Test results on a Beijing traffic dataset show that the SARI-MA–SVM model can improve accuracy and reduce errors in traffic prediction. The obtained pre-diction fits well with the measured data. Therefore, the SARIMA–SVM model can fully characterize traffic variations and is suitable for passenger flow prediction.

III. METHODOLOGY

Deep learning algorithms fall into the category of unsupervised algorithms, and they rely on a neural network to achieve their impressive outcomes. So ,we use deep learning with long short-term memory, RNN, and greedy layer-wise algorithm. We will pick up the best performing algorithm as a final algorithm to predict the model in production.

The data is supplied as Comma–Separated Values (CSV). That data is uploaded into the application which has a neural network pattern recognition mechanism domestically, where this will establish a cluster using a greedy approach, after its synthesis in long short-term memory and wraps the synthesis data to the recurrent neural network to give output visual analysis and statistical modeling of passengers forecasting.

YOLOv3

YOLOV3 is an object detection algorithm that stands for "You Only Look Once version 3". It is a deep learning-based algorithm that uses convolutional neural networks (CNN) to detect and locate objects within an image. YOLOv3 is the latest version of the YOLO family of object detection models.

YOLOv3 uses a single neural network to process the entire image at once and predicts the bounding boxes and class probabilities for each object in the image. It is capable of detecting objects in real-time and can handle multiple objects in the same image. YOLOv3 is known for its speed and accuracy in object detection tasks, making it a popular choice for many computer vision applications.

The YOLOv3 algorithm uses a feature extractor based on a Darknet-53 network and includes some improvements over its previous version, YOLOv2. YOLOv3 introduced various changes like a different backbone, upsampling layers, and new techniques for training the network.

YOLOv3 is an open-source project and is implemented in various programming languages, including Python and C++. It is widely used in various applications, such as autonomous driving, surveillance systems, and robotics.

OBJECT RECOGNITION:

Object recognition refers to the ability of computer algorithms to identify and classify objects in digital images or videos. This is a fundamental task in computer vision and artificial intelligence.

Object recognition algorithms typically use machine learning techniques, such as deep neural networks, to learn from large datasets of labelled images. These algorithms analyse the visual features of an image, such as colour, texture, shape, and size, to identify and classify objects within it.

Augmented reality: Object recognition can be used to overlay digital information onto real-world objects in augmented reality applications.

Security and surveillance: Object recognition can be used for detecting and tracking suspicious activities or individuals in security and surveillance systems

Object recognition technology is rapidly advancing and has the potential to revolutionize many industries and applications.

Medical imaging: Object recognition can assist in medical diagnosis by automatically identifying and analysing anatomical structures in medical images

RNN

RNN stands for Recurrent Neural Network, which is a type of artificial neural network designed to handle sequential data such as time series, natural language processing, and speech recognition.

Unlike traditional neural networks, which process input data in a fixed and predefined way, RNNs allow for feedback loops, which enable them to process sequential data by maintaining a state or memory of previous inputs. This makes RNNs particularly well-suited for tasks that require temporal or sequential analysis.

The key feature of RNNs is their ability to use the output from previous time steps as inputs for the current time step, allowing them to learn from the sequence of input data. This makes RNNs particularly useful for tasks such as natural language processing, where the meaning of a word or phrase depends on the context of the surrounding words.

There are several variants of RNNs, such as Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRU) networks, which have been developed to address some of the limitations of traditional RNNs, such as the vanishing gradient problem.

CAMSHIFT

Camshift is a computer vision algorithm used for object tracking in video sequences.The Camshift algorithm works by initially selecting a region of interest (ROI) in the first frame of a video sequence, which is typically the location of the object to be tracked. The histogram of colours within the ROI is then calculated, which is used as a probability distribution for the object's colour. This histogram is then back-projected onto the subsequent frames of the video, which results in a probability map of where the object might be located.

The mean shift algorithm is then applied to the probability map to find the peak of the distribution, which represents the object's current location. The size and shape of the ROI are then adapted to the object's new location by computing the moments of the probability distribution. This process is repeated for each frame of the video sequence, resulting in a continuously adaptive tracking system.

One of the advantages of the Camshift algorithm is that it is able to handle changes in the size and orientation of the tracked object. It can also handle partial occlusion of the object, as long as enough of the object is visible for the algorithm to compute the colour histogram.

However, the Camshift algorithm does have limitations. It is sensitive to changes in lighting conditions, which can cause the colour histogram to change over time. It also struggles with tracking objects that move quickly or change shape significantly over time.

VGG-16

VGG-16 architecture has 16 layers, including 13 convolutional layers and 3 fully connected layers, and it has been widely used for image classification tasks.The VGG-16 architecture has a number of notable features:

The use of small 3x3 convolutional filters: The VGG-16 architecture uses a series of 3x3 convolutional filters throughout the network, which allows it to learn more complex features and reduces the number of parameters in the model.

Stacking of multiple convolutional layers: The VGG-16 architecture stacks multiple convolutional layers on top of each other, which increases the depth of the network and allows it to learn more abstract features.

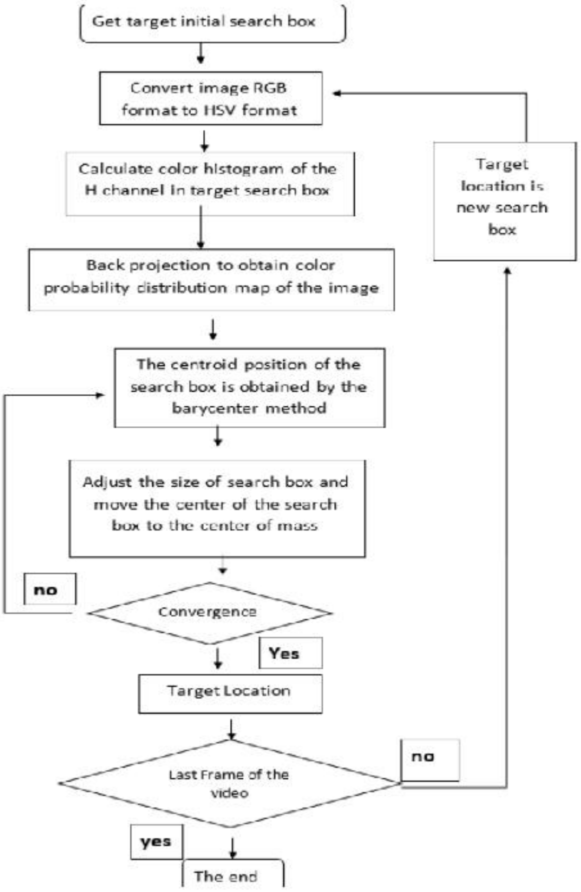
Use of max pooling: The VGG-16 architecture uses max pooling after every two or three convolutional layers, which reduces the spatial resolution of the feature maps and helps the network to be more invariant to small spatial translations.

Fully connected layers: The VGG-16 architecture ends with three fully connected layers that perform the classification task.

The VGG-16 architecture has achieved state-of-the-art performance on a number of image classification tasks, including the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) in 2014, where it achieved a top-5 error rate of 7.3%. The VGG-16 architecture has also been used as a base for many other CNN architectures, such as the VGG-19, Inception-V1, and Inception-V2 architectures.

LSTM (Long Short-Term Memory) and RNN (Recurrent Neural Network) are both types of artificial neural networks that can be used for predicting people's behaviour based on historical data. The key advantage of using LSTM and RNN over traditional statistical methods is their ability to capture temporal dependencies and patterns in sequential data.

To predict people using LSTM and RNN, the following steps are typically involved:



Data preparation: The first step is to collect and prepare the historical data. This may include data such as user interactions on a website, customer purchase history, or social media activity. The data is typically divided into training and testing sets.

Data pre-processing: The data may need to be pre-processed, such as normalization or scaling, to ensure that the data is consistent and suitable for training the model.

Model training: The LSTM or RNN model is trained on the training data to learn the temporal patterns and dependencies in the data.

Model evaluation: The trained model is then evaluated on the testing data to measure its performance and accuracy.

Predictions: Once the model is trained and evaluated, it can be used to make predictions on new data, such as predicting customer behaviour or website user engagement.

Some examples of predicting people using LSTM and RNN include predicting user behaviour on websites, predicting customer churn in business, and predicting stock prices based on historical data.

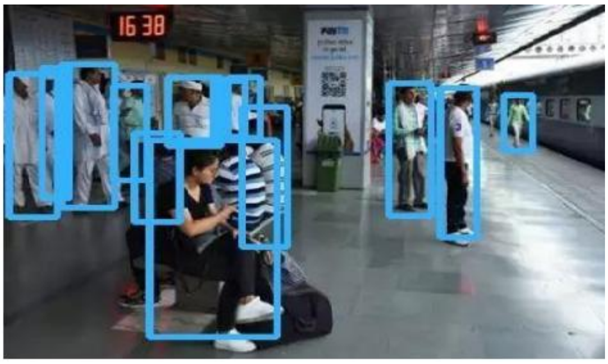


Fig. 1 A sample image of detecting and plotting the people

Image classification is a subfield of computer vision that involves the categorization of images into predefined classes or categories. The goal of image classification is to automatically assign a label or category to a given image based on its visual content. This task is typically performed using machine learning algorithms, such as deep neural networks.

The process of image classification involves several steps:

Data collection: A large dataset of images with known labels is collected. These images are typically labelled manually by human annotators.

PREPROCESSING: The collected images are pre-processed to extract useful features from them, such as colour, texture, and shape. This step may involve resizing, cropping, or filtering the images.

TRAINING: A machine learning model is trained on the pre-processed images. This typically involves using a deep neural network, such as a convolutional neural network (CNN), which is designed to extract high-level features from images.

VALIDATION: The trained model is evaluated on a separate validation dataset to determine its accuracy and performance. This step is important for detecting and correcting overfitting, which occurs when the model is too complex and has learned to memorize the training data rather than generalizing to new data.

TESTING: The final step involves using the trained model to classify new images. This step requires the input of an unseen image to the model and obtaining a classification label from it.

I mage classification has numerous applications, such as image search engines, medical image diagnosis, autonomous vehicles, and more. However, achieving high accuracy in image classification often requires a large and diverse dataset, powerful hardware, and significant computing resources.

IV. CONCLUSION

In this project with the video images a statistical study on the detection of passenger getting on and off of the public transport is analysed. First the head target image samples were collected through a variety of ways. Head target detection model based on YOLOv3 is used. Combined with the constraint, a judgement rule of passenger position information is given to improve the reliability of passenger tracking. Finally based on the curve of passenger head trajectory, this system studies the judgement method of passenger boarding and alighting behaviour and propose a statistical algorithm foe passenger detection of public transport boarding and alighting which is verified by a variety of time period.

REFERENCES

[1] JianyuanGuo , Zhen Xie , Yong Qin , Limin Jia , And Yaguan Wang, “Short-Term Abnormal Passenger Flow Prediction Based on the Fusion of SVR and LSTM”, IEEE 2019.

[2] Yifan Tan, Haixu Liu, Yun Pu, Xuemei Wu and Yubo Jiao, “Passenger flow prediction of integrated passenger terminal based on K-Means-GRNN” 2021.

[3] Wei Li, Liying Sui, Min Zhou &Hairong Dong, “Short term passenger flow forecast for urban rail transit based on multi source data” 2021.

[4] Jitao Li,ChuguiXu,YongquanLiang,GengkunWu,and Zhao Lian, “An RBF Neural Network Clustering Algorithm based on K-Nearest Algorithm” 2022.

[5] Min Gong,XiangFeiZh,i Hu Wang,Yun Jie Qiu, “Sequential Framework for ShortTerm Passenger Flow Prediction at Bus Stop” 2014.

[6] Asiye Baghbani , Nizar Bouguila, Zachary Patterson, “Short term passenger flow prediction using a bus network graph convolutional long short term memory neural network model” 2022.

[7] Jinlei Zhang, Feng Chen, Zhiyong Cui, Yinan Guo, and Yadi Zhu “ Deep learning Architecture for Short-term Passenger Flow Forecasting in Urban Rail Transit” [2019].

[8] T. Kunimatsu & C. Hirai "The prediction of passenger flow under transport disturbance using accumulated passenger data"[2014].

[9] Y. Wei and M.-C. Chen, ‘‘Forecasting the short-term metro passenger flow with empirical mode decomposition and neural networks,’’ Transp. Res. C, Emerg. Technol., vol. 21, no. 1, pp. 148–162, 2012.

[10] J. Yang and Z. Hou, ‘‘A wavelet analysis based LS-SVM rail transit passenger flow prediction method,’’ China Railway Sci., vol. 34, no. 3, pp. 122–127, 2013.

[11] J. Z. Zhou and D. Y. Zhang, ‘‘Direct ridership forecast model of urban rail transit stations based on spatial weighted LS-SVM,’’ J. China Railway Soc., vol. 36, no. 1, pp. 1–7, 2014.

[12] Y. Sun, B. Leng, and W. Guan, ‘‘A novel wavelet-SVM short-time passenger flow prediction in Beijing subway system,’’ Neurocomputing, vol. 166, pp. 109–121, Oct. 2015.

[13] Y. Sun, G. Zhang, and H. Yin, ‘‘Passenger flow prediction of subway transfer stations based on nonparametric regression model,’’ Discrete Dyn. Nature Soc., vol. 2014, Apr. 2014, Art. no. 397154.

[14] Y. Li, X. Wang, S. Sun, X. Ma, and G. Lu, ‘‘Forecasting short-term subway passenger flow under special events scenarios using multiscale radial basis function networks,’’ Transp. Res. C, Emerg. Technol., vol. 77, pp. 306–328, Apr. 2017.

[15] C.-F. Chen, Y.-H. Chang, and Y.-W. Chang, ‘‘Seasonal ARIMA forecasting of inbound air travel arrivals to Taiwan,’’ Transportmetrica, vol. 5, no. 2, pp. 125–140, 2009.

[16] M. M. Hamed, H. R. Al-Masaeid, and Z. M. B. Said, ‘‘Short-term prediction of traffic volume in urban arterials,’’ J. Transp. Eng., vol. 121, no. 3, pp. 249–254, 1995.

[17] F. Crawford, D. P. Watling, and R. D. Connors, ‘‘A statistical method for estimating predictable differences between daily traffic flow profiles,’’ Transp. Res. B, Methodol., vol. 95, pp. 196–213, Jan. 2017.

[18] N. G. Polson and V. O. Sokolov, ‘‘Deep learning for short-term traffic flow prediction,’’ Transp. Res. C, Emerg. Technol., vol. 79, pp. 1–17, Jun. 2017.

[19] L. Nie, D. Jiang, L. Guo, and S. Yu, ‘‘Traffic matrix prediction and estimation based on deep learning in large-scale IP backbone networks,’’ J. Netw. Comput. Appl., vol. 76, pp. 16–22, Dec. 2016.

[20] X. Ma, Z. Tao, Y. Wang, H. Yu, and Y. Wang, ‘‘Long short-term memory neural network for traffic speed prediction using remote microwave sensor data,’’ Transp. Res. C, Emerg. Technol., vol. 54, pp. 187–197, May 2015.