Journal of Information Systems and Informatics
Vol. 7, No. 3, September 2025 e-ISSN: 2656-4882 p-ISSN: 2656-5935
DOI: 10.51519/journalisi.v7i3.1159 Published By DRPM-UBD

LSTM Forecasting and K-Means Clustering for Passenger Mobility Management at Bus Terminals

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Abstract

Rapid urban population growth has increased the need for efficient public transportation systems, particularly at bus terminals as major mobility hubs. To address operational challenges such as traffic congestion and limited infrastructure, this study proposes an innovative data-driven approach. A hybrid model is applied, integrating Long Short-Term Memory (LSTM) for passenger volume forecasting and K-Means Clustering for mobility pattern segmentation at the Jepara Bus Terminal. Monthly passenger data was utilized, and the K-Means method was applied to group monthly mobility patterns into three categories: low, medium, and high. The optimal cluster selection (k=3) was based on the highest Silhouette score of 0.785, providing clear seasonal insights. Analysis results indicate that September is the peak mobility period, while months like January and February fall into the low category. Furthermore, an LSTM model was trained to predict future passenger volumes. The model's performance was carefully validated and proven accurate, with a Mean Squared Error (MSE) of 0.0304 and a Root Mean Squared Error (RMSE) of 0.1745. These findings confirm that the model is reliable in capturing complex passenger movement patterns. Overall, this study concludes that the combination of LSTM and K-Means is an effective solution for supporting proactive decision-making. The results of this study can assist terminal managers in optimizing resource allocation and formulating more adaptive operational strategies, thereby contributing to the development of a more responsive and efficient intelligent transportation system.

Keywords: Smart Transportation; Principal Component Analysis; Mobility Pattern Segmentation; Public Transport Optimization; Data-Driven Decision Support

1. INTRODUCTION

Rapid and massive population growth in urban areas has driven an increase in the need for public transportation systems that are efficient and responsive to the complex dynamics of urban mobility. One of the most affected sectors is bus terminal operations, which are vital public transportation network nodes. Massive urbanization directly affects the surge in demand for daily mobility services, which triggers serious challenges such as traffic congestion, limited capacity and supporting facilities at terminals, and low levels of integration between

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

transportation modes, such as buses, trains, and app-based transportation services [1], [2].

Amidst the accelerating digital transformation, various app-based mobility services and on-demand transportation concepts have emerged and increasingly dominate the preferences of urban communities [3], [4]. This has forced conventional public transportation systems—including bus terminal operations—to make rapid adjustments to remain relevant, competitive, and user-centric. Given urban mobility's highly dynamic and unpredictable nature, these challenges require a more adaptive and technology-based management approach [5].

As hubs for inter-regional movement and transfers within the land transportation network, bus terminals often face serious issues related to excessive passenger density, especially during peak hours or holiday seasons [6]. The high volume of passenger movement that exceeds the physical capacity of the terminal facilities often results in reduced comfort and decreased safety levels for users. Common challenges include unstructured movement circulation, long queues without an automatic queuing system, limited waiting areas, and basic facilities such as toilets, seating, and information points [1], [7], [8].

These issues become more complex when traffic flow management around the terminal is not integrated with real-time monitoring systems [8], [9]. Many terminals have not yet adopted sensor-based technology, innovative CCTV, or monitoring dashboards that can provide real-time information on vehicle and pedestrian density and circulation. As a result, traffic management and passenger movement regulation processes are still manual and inefficient, increasing the potential for congestion, accident risks, and a decline in overall service quality.

A similar phenomenon can be observed at various terminals in Indonesia. For example, a study on passenger volume forecasting for the Jakarta Busway (Transjakarta) highlights the importance of accurate predictions to maintain user satisfaction and optimize fleet expansion and new route openings [10]. However, Jepara Bus Terminal still lags behind in terms of management and infrastructure, given its status as a Type C terminal. The operational system used tends to be reactive rather than predictive—an approach commonly found in many regional terminals. This situation is further exacerbated by significant fluctuations in passenger volume each month, such as sharp spikes in September, which often overwhelm available capacity and resources, leading to inefficiencies. Unlike transportation terminals in major cities such as Jakarta Bus Terminal, which rely on real-time monitoring and data analysis for dynamic operational adjustments, Jepara Terminal still relies on manual systems and conventional methods to run its daily operations.

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

To address these challenges effectively, a data-driven management strategy is needed to provide predictive and segmented insights into passenger movement [11], [12]. In this context, data-driven forecasting technology based on historical data and algorithm-assisted segmentation systems offer potential solutions to support operational efficiency and long-term strategic planning. Passenger volume forecasting—intense learning models such as Long Short-Term Memory (LSTM)—can help predict density trends based on specific time patterns, such as weekdays, weekends, holiday seasons, or special events [13], [14].

Meanwhile, mobility pattern segmentation using clustering techniques like K-Means enables grouping passengers based on their travel characteristics, such as travel frequency, travel time, or the mode of transportation used [2], [4]. In this way, terminal operators can design more personalized and adaptive service policies, such as flexible departure schedules, dedicated fast lanes for regular passengers, or adjusting fleet capacity based on the specific needs of particular groups. Supporting technologies such as IoT sensors, Wi-Fi data, and mobile tracking applications can also obtain real-time information on passenger inflows and outflows, enabling terminal management to become more proactive and evidence-based [9], [15].

Although numerous studies have been conducted in public transportation and technology integration, most research remains limited to conceptual levels or focuses solely on route optimization and fleet management. Few studies have directly implemented deep learning models like LSTM for dynamic and contextual passenger volume forecasting at bus terminals. Additionally, passenger segmentation approaches are rarely applied in terminal operational practices despite their significant potential to create more adaptive and responsive services tailored to passenger needs [2], [4] . This gap opens up significant research opportunities, particularly in designing artificial intelligence-based terminal management systems that automatically adjust operational strategies based on identified mobility patterns.

Through an integrative approach combining LSTM forecasting and K-Means segmentation, this study aims to develop a predictive analysis model capable of accurately predicting passenger mobility patterns at Jepara Bus Terminal. From a scientific perspective, this research enriches the academic literature on applying machine learning methods in the public transportation sector, particularly in the context of urbanization and land transportation facility management. This research also addresses the need for predictive models that are not only based on historical data but also adaptive to changes in environmental conditions and user behavior.

Practically, the results of this study are expected to serve as a foundation for more informed decision-making by terminal managers and local governments. Terminal operators can optimize resource allocation, establish more efficient operational

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schedules, and improve overall passenger service quality using predictive and segmentation approaches. Additionally, integrating forecasting results with information technology-based management systems can enhance accuracy in responding to mobility fluctuations, minimize the potential for congestion, and accelerate service adjustments to meet the evolving needs of users.

2. LITERATURE REVIEW

People have been using traditional forecasting methods like ARIMA (Autoregressive Integrated Moving Average) and Prophet for a long time to guess how many people will travel, how much traffic there will be, and how people will move around in their communities. These methods have worked well in some cases, but their flaws are becoming more and more clear when they are used on urban transportation systems that are constantly changing and are very complicated. Recent research has shown that ARIMA and Prophet aren't very good at finding non-linear data patterns or handling long-term dependencies in time series data [16]. This makes predictions less accurate, especially in cities where things change quickly because of things like the weather, local events, or sudden changes in transportation policy.

The Long Short-Term Memory (LSTM) model is a better option than traditional methods because it overcomes their limitations. LSTM is a type of artificial neural network that is good at processing time series data and figuring out long-term relationships between events [17]. LSTM is much better at avoiding the vanishing gradient problem than traditional neural networks. This lets it capture complex and unstable movement patterns in mobility data [16], [18], [19]. When used in transportation systems, LSTM has been shown to make more accurate predictions, especially when dealing with changes in the number of passengers, changes in routes, and changes in travel patterns over time [16], [19].

The data segmentation step is just as important for making predictions accurate. K-Means Clustering is a common way to group data based on certain shared traits. It is one of the most common ways to segment data. This method is useful for looking at and grouping passenger behavior based on things like travel time, where they are going, or the patterns of their routes [16], [18], [20]. K-Means makes the data structure clearer and improves the quality of the input data that prediction models like LSTM use [18], [19], [20]. When clustering is done correctly, the model training process is faster and the predictions are more accurate because the model only looks at data from groups that are similar.

Recent research shows that using the LSTM and K-Means algorithms together makes predictions more accurate than using them separately. This way of combining K-Means and LSTM lets K-Means filter and group the data into a few

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groups that are all the same before LSTM makes the predictions. This method has worked well in a number of studies, such as predicting vehicle loads and analyzing travel patterns, where the predictions are more accurate and stable [16], [18], [19], [20]. These two methods have also been used in other transportation applications, like ship navigation, managing the temperature in cold chain logistics, and estimating energy use in cities. This shows that they can be used in a wide range of smart transportation areas [16], [18], [20], [21].

As the need for transportation systems that are data-driven and responsive grows, combining LSTM and K-Means can help from both a technical and a policy point of view. This method lets transportation managers make service plans based on accurate predictions, like dynamic scheduling, better fleet allocation, and more flexible management of passenger density. In the academic world, this method opens up a lot of research possibilities for creating hybrid machine-learning models for smart cities and transportation systems of the future. So, using LSTM and K-Means is a new way to do things that is very important for making the urban transportation system more creative, useful, and focused on the needs of users.

3. METHODS

This research uses a quantitative approach with a case study method at the Jepara Bus Terminal. The data obtained comes from the Jepara Regency Transportation Office, which is publicly available through the official application of the Jepara Central Bureau of Statistics at the link: https://jeparakab.bps.go.id/id/statistics-table/1/ODMyIzE=/banyaknya-lalu-lintas-kendaraan-umum-di-terminal-bus-jepara--2023.html in the form of total passengers recorded every month during a specific period. The research process consists of four main stages: data cleaning and pre-processing, passenger segmentation using the K-Means algorithm, dimension reduction via Principal Component Analysis (PCA) for cluster visualization, and forecasting future passenger numbers using the Long Short-Term Memory (LSTM) model. The complete flow of the method is shown in Figure 1.

3.1. Data Cleaning

The data was obtained from the Jepara Regency Transportation Agency in CSV format, which includes the number of passengers arriving and departing for each mode of transportation per month. At this stage, the raw data requires pre-processing to ensure quality and consistency. Some data entries have blank values or use a hyphen ('-') in the number column. This data is handled by replacing the hyphen character with zero, then all columns related to passenger numbers are converted to a numerical format. Next, adjustments were made to the data structure. The data headers, consisting of two rows, were manually combined to

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form more descriptive column names, such as 'BUS_ARRIVAL' and 'BUS_DEPARTURES'. Irrelevant rows, such as the total row and rows with empty values (NaN) in the MONTH column, were removed to maintain data integrity. After the data was cleaned, the TOTAL_PASSENGERS variable was calculated by summing the number of passengers arriving and departing each month, which then became the primary focus for segmentation and forecasting. This approach ensures that the data used for analysis is clean, complete, and ready for further processing by the model.

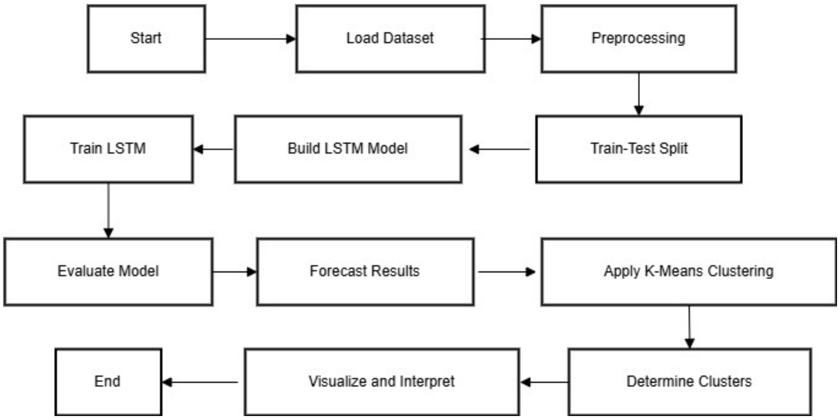

Figure 1. Workflow of passenger mobility forecasting and segmentation

3.2. Segmentasi K-Means

K-Means Clustering was applied to group months in a year based on passenger mobility patterns. K-Means is an unsupervised machine learning algorithm, meaning that the data is not labeled beforehand - the system automatically looks for patterns or groups (clusters) in the data [22]. This algorithm divides data into (k) clusters, with members in one cluster having similar characteristics. The minimized objective function of K-Means is the sum of the squares of the distances between each data point and its nearest cluster center, as shown in Equation 1.

$$J=\sum_{i=1}^{k}\sum_{x_j \in S_i} | x_j - \mu_i |^2 \quad (1)$$

The selection of the number of clusters (k) was based on testing several scenarios and evaluated using the Silhouette Score, a metric that measures how similar members within a cluster are to one another and how different they are from other clusters. Based on the tests conducted, the highest Silhouette Score was obtained at k=3, with a score of 0.785. This value indicates that dividing the data into three

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clusters is the most optimal and effective configuration. Therefore, the value k=3 was selected for mobility pattern segmentation, resulting in descriptive and relevant categories for terminal managers, namely low, medium, and high mobility. Combining K-Means with time forecasting techniques can improve the accuracy of predicting conditions that require a predetermined number of clusters, which can affect the results [23].

3.3. PCA Visualization

To make the segmentation results more straightforward to understand, dimensionality reduction using Principal Component Analysis (PCA) is performed. PCA is a multivariate statistical technique that reduces the dimensionality of large data sets while maintaining interpretability and minimizing information loss by generating new uncorrelated variables that capture the variance of the original data [24]. PCA serves to project high-dimensional data into two main dimensions while retaining as much information or variation in the data as possible [25]. This allows cluster results to be visualized intuitively in the form of a two-dimensional graph. Recent studies have explored PCA in Rieman manifolds, enabling effective dimensionality reduction in spaces with varying curvature, such as hyperbolic and spherical geometries [26].

In PCA visualization, a stage is needed to help visualize the results of K-Means segmentation. Segmentation aims to group the months of the year into several mobility categories, such as low, medium, and high. Steps are taken by inputting public vehicle transportation data, each of which has an arrival and departure flow. All features are put into a feature matrix X, which is then standardized using Scikit-Learn's SrandardScaler method, as in Equation 2.

$$Z=\frac{X-\mu}{\sigma} \tag{2}$$

After the data is standardized, a dimension reduction process is performed using PCA. In this study, PCA was configured to extract two principal components (n_components = 2). The aim is to simplify the complexity of the data but also to facilitate visualization of the segmentation results in two dimensions. The covariance matrix $Cov(X)$ is calculated as in Equation 3, and the data is reduced in dimension X_{PCA} as in Equation 4.

$$Cov(X)=\frac{1}{n-1}(X-\bar{X})^T(X-\bar{X}) \tag{3}$$

$$X_{PCA}=X\cdot W \tag{4}$$

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The next step is to apply the K-Means Clustering algorithm to the PCA transformation results. This algorithm is used to group the data into three clusters (n_clusters = 3) based on pattern similarity. The initialization process is done randomly, and the iteration is done until the centroid position is taken. Due to the uneven distribution of some initial features, an additional approach of logarithmic transformation of the initial features, i.e., the logarithm of (value + 1), was performed to avoid errors when processing zero values, as in Equation 5.

$$X_{log} = log(1+X) \tag{5}$$

After the logarithmic transformation is applied, the whole process is re-standardized on the new data. The final PCA results are stored in two new columns, PCA1 and PCA2, which represent the two principal components of the dimensionality reduction results. To clarify the segmentation results, a two-dimensional visualization was created using Plotly Express. This interactive scatter plot displays each point as a representation of the month, positioned based on the PCA1 and PCA2 values and colored according to the cluster.

3.4. LSTM Forecasting

The Long Short Term Memory (LSTM) model is used for time series data modeling due to its ability to capture long-term dependencies and complex temporal relationships [27]. The research continues to the time series forecasting stage using Long Short-Term Memory (LSTM), a Recurrent Neural Network (RNN) architecture that is very effective for handling time series data such as monthly passenger trends. LSTMs are specifically designed to overcome the limitations of conventional RNNs in capturing long-term relationships in sequential inputs [28]. With this design, the LSTM can remember long-term patterns that appear in public transportation data.This can be seen in Figure 2.

The time series data, TOTAL_PASSENGERS, is normalized using MinMaxScaler so that all values are within the range of 0 - 1 so as to speed up the learning process. The dataset is then formed in a sliding window format with time-step = 3. Next, the data is organized in a sliding window format to learn the relationship model between the previous three months and the month to be predicted. The Long Short-Term Memory (LSTM) model is trained for 100 - 200 epochs, with a batch size of 16. After training, the model is used to predict the number of passengers 6 months ahead.

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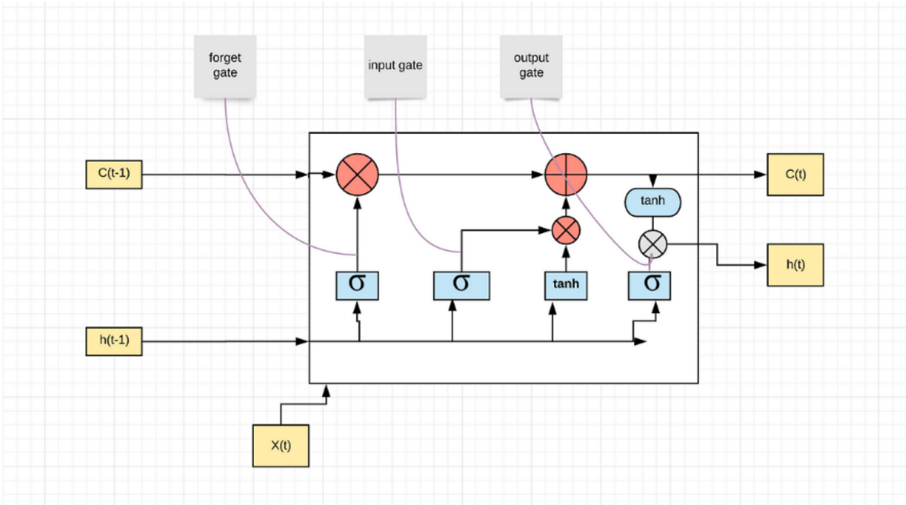

Figure 2. Forecasting using LSTM

During the training process, model performance was rigorously evaluated using Mean Squared Error (MSE). This metric was chosen to measure the average square of the difference between the predicted value $\hat{y}$ and the actual value y. The mathematical formulation of MSE is given by Equation 6.

$$MSE=\frac{1}{N}\sum_{i=1}^{N}\left(y_i-\hat{y}_i\right)^2 \tag{6}$$

$$\mathrm{RMSE}=\sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(y_i-\hat{y}_i\right)^2} \tag{7}$$

$$MAE=\frac{1}{N}\sum_{i=1}^{N}\left|y_i-\hat{y}_i\right| \tag{8}$$

The consistent decrease in MSE values during the training process indicates that the LSTM model is capable of learning and recognizing complex time patterns in historical data. To provide a more comprehensive overview of the model's prediction accuracy, additional evaluation metrics such as RMSE (Root Mean Squared Error) and MAE (Mean Absolute Error) were also used. From the results obtained, the MSE value is 0.0353, RMSE is 0.1878, and MAE is 0.1528.

3.5. Equipment used and time required

In this study, the entire model development and training process was conducted using Python programming. Google Colab was used as the main platform, along with Scikit-learn and NumPy for data pre-processing and numerical manipulation.

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The hardware specifications used for model training are:

1) Processor (CPU) : AMD Ryzen 5 Pro 4650U with Radeon Graphics (12 CPU).
2) Memory (RAM) : 238.46 GB.

The training time for the LSTM model varies depending on the configuration of hyperparameters such as the number of epochs (100-200) and batch size (16). Each model training session takes about 3 minutes to converge, ensuring that the model learns effectively from historical data.

4. RESULTS AND DISCUSSION

4.1. Experimental Performance

Based on data obtained from the Jepara Regency Transportation Office, passenger mobility patterns at the Jepara Bus Terminal show a significant variation in the number of passengers each month. The types of vehicles recorded include buses, microbuses, pickups, public transportation, rural transport both arrival and departure dates. This can be seen in Table 1.

Table 1. Data table

Bus		**MicBus**		**Pickup**		**Publik Trans**		**Rural Trans**		**Total**	
Arr	Dep	Arr	Dep	Arr	Dep	Arr	Dep	Arr	Dep	Arr	Dep
885	841	7072	6789	0	0	228	216	190	182	8375	8029
806	766	6444	6186	0	0	208	197	173	166	7631	7316
906	861	7241	6951	0	0	233	222	194	187	8574	8220
828	787	6619	6354	0	0	213	203	178	171	7837	7514
889	844	7103	6819	0	0	229	217	191	183	8411	8064
1316	1293	13055	12533	0	0	421	400	350	336	15187	14562
1487	1413	14266	13695	0	0	460	437	383	368	16596	15912
1607	1526	15412	14795	0	0	496	472	414	397	17929	17191
2853	2711	27371	26276	0	0	882	838	735	705	31840	30529
1508	1433	14464	13886	0	0	466	443	388	373	16826	16134
1355	1287	12998	12478	0	0	419	398	349	335	15121	14498
1285	1221	12330	11837	0	0	397	377	331	318	14343	13753
15770	14983	144375	138599	0	0	4420	4420	3876	3721	168670	161722

From the preliminary visualization results, it can be seen that September is the period with the highest number of passengers. Meanwhile, February tends to have a lower volume of passengers, a factor that could be due to weather or holidays that could cause a surge. This issue can be addressed by using monthly categorization based on passenger traffic density so that terminal operational management can be adjusted. The number of passengers per month is shown in Figure 3.

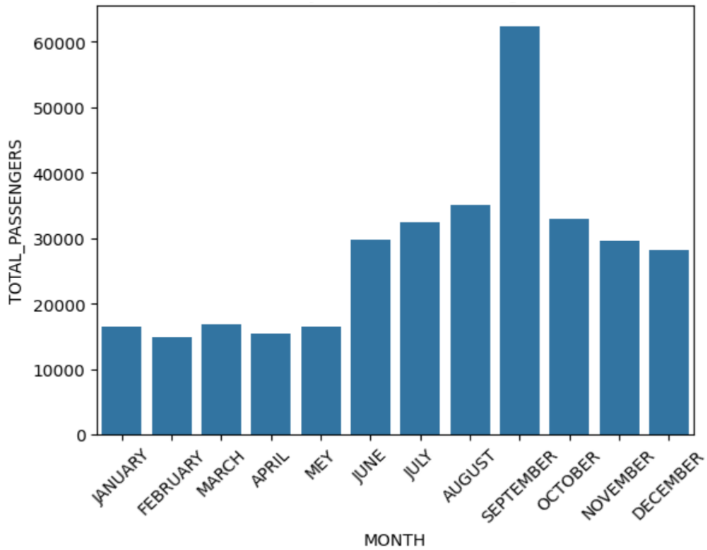

Figure 3. Number of passengers per month

To group these mobility patterns, the K-Means Clustering method was applied. The selection of the number of clusters (k) was evaluated using the Silhouette Score. Based on the test, the highest Silhouette Score (0.785) was achieved at k=3, confirming that three clusters are the optimal choice for this data. The value k=3 was chosen to provide a more detailed operational categorization, namely Low, Medium, and High. The results of the Silhouette Score evaluation for various numbers of clusters can be seen in Table 2.

Table 2. Silhouette scores for various cluster counts in K-Means Clustering

Number of Clusters (k)	Silhouette Score
2	0.661
3	0.785
4	0.725

Principal Component Analysis (PCA) cluster visualization helps show the distribution between clusters in a two-dimensional space, making it easier to understand for policymakers. The data used for clustering are eight features of the number of vehicles based on the fund type of movement direction. All data were logarithm transformed using $\log(1 + x)$ to overcome the non-normal distribution, then standardized with Z-score so that the features have a balanced scale.

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The PCA scatter plot visualization Figure 4 shows that the three clusters are well separated, indicating the success of the mobility pattern grouping. These clusters map the months of the year into different mobility categories, such as September, which has the highest passenger volume and is identified as a cluster with high mobility.

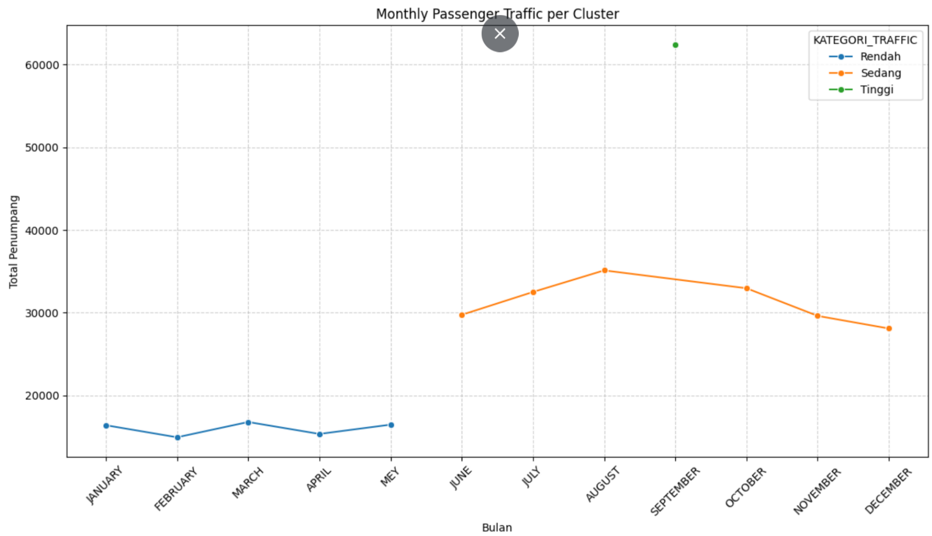

Figure 4. Visualisasi of passenger mobility clusters using PCA and K-Means

The next step is to build a predictive model to estimate the number of passengers in a specific period. The model that will be used is Long Short-Term Memory (LSTM), which is a type of Recurrent Neural Network (RNN) designed to handle patterns in time series data, especially those containing long-term dependencies. In forecasting the number of passengers for the next 6 months, 39.321 million people were recorded, indicating that LSTM has proven effective for predicting the future.

The data used in model training is the TOTAL_PASSENGER time series per month, which has been normalized using MinMaxScaler to speed up the learning process and reduce the risk of bias. By using a sliding window approach and a time-step of three, the LSTM model can learn from the previous three months to predict the number of passengers in the following month.

Table 3. LSTM Forecasting Model Performance Evaluation Results

Evaluation Metric	Value
Mean Squared Error (MSE)	0.0304
Root Mean Squared Error (RMSE)	0.1745
Mean Absolute Error (MAE)	0.1456

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The constructed LSTM model consists of one 64-unit LSTM layer and one Dense output layer. Model training was conducted for 100 to 200 epochs. During the training process, model performance was rigorously evaluated using Mean Squared Error (MSE). This metric was chosen to measure the average square of the difference between the predicted value $\hat{y}$ and the actual value y. The consistent decrease in MSE values during the training process indicates that the LSTM model is capable of learning and recognizing complex time patterns in historical data. To provide a more comprehensive overview of the model's prediction accuracy, additional evaluation metrics such as RMSE (Root Mean Squared Error) and MAE (Mean Absolute Error) were also used. From the results obtained, the MSE value is 0.0353, RMSE is 0.1878, and MAE is 0.1528, can be seen in Table 3.

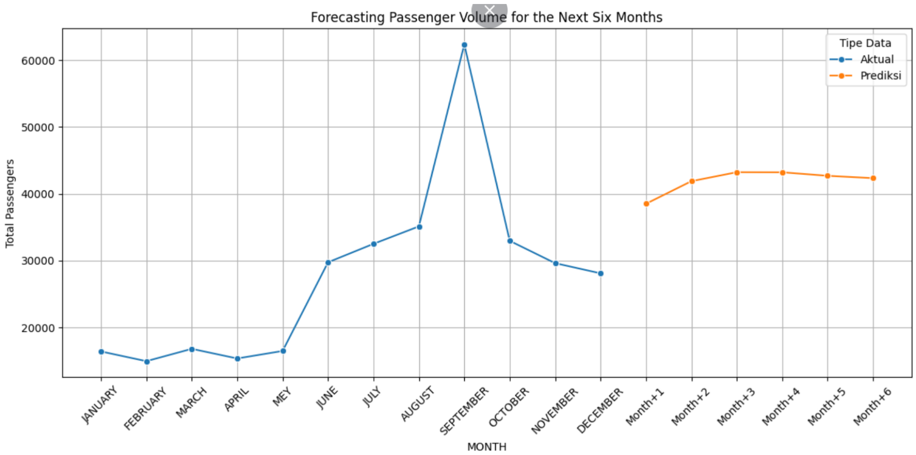

Figure 5. Forecasted passenger volume for the next six months

Figure 5 shows a comparison of actual monthly passenger volumes and LSTM model forecasts for the next six months. From this visualization, it can be seen that the model successfully captures the fluctuation patterns in the historical data, including spikes in certain months. After the actual data ends in December, the model predicts passenger volumes that tend to be stable or slightly increasing. These predictions are consistent with the seasonal patterns identified by the model, providing valuable insights for short- to medium-term operational planning.

In this research, it is evident that the integration between the LSTM forecasting method and K-Means segmentation provides valid results for Jepara bus terminal managers. Segmentation helps in grouping busy and non-peak operational periods, while the LSTM model provides predictive guidance that can be used for short-term planning. This finding is in line with previous research, which shows that machine learning and deep learning-based approaches have great potential to be applied in the management of public transportation systems [29], [30].

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

4.2. Discussion

The K-Means clustering results effectively answered the research objectives related to passenger mobility segmentation by identifying three distinct mobility clusters: Low, Medium, and High. Based on the PCA visualization, September consistently fell within the high mobility cluster, indicating a peak period of passenger activity. Conversely, months such as January and February tended to fall within the low mobility cluster.

This categorization provides significant practical benefits for the management of Jepara Bus Terminal. During months with high mobility, management can consider increasing bus frequency, allocating additional staff at ticket counters and waiting areas, and enhancing facility capacity to avoid congestion and passenger inconvenience. During periods of moderate mobility, operations can run normally, though monitoring is still required to anticipate sudden changes. Meanwhile, months with low mobility can be utilized for bus fleet maintenance schedules, staff training, or terminal infrastructure improvements without significantly disrupting services.

The LSTM model did a great job of predicting how many passengers there would be. The Mean Squared Error (MSE) value of the model went down steadily during training, which showed that the model was good at finding time series patterns in historical data. The trend analysis of the 6-month forecast graph showed patterns that were similar to past data, such as possible increases or decreases in the number of passengers. These predictions greatly support operational decisions. For example, forecasts of passenger surges in certain months give management enough time to prepare, such as ordering additional buses or arranging staff shifts. The model's ability to provide short- to medium-term predictions enables more proactive and efficient planning.

This study is in line with similar research showing the effectiveness of LSTM in predicting passenger numbers in the context of public transportation. For example, a survey by [10] demonstrated the ability of LSTM in predicting the volume of passengers on the Jakarta Busway, confirming the relevance of this deep learning model in urban transportation management. The consistency of these results reinforces the argument that deep learning-based models, such as LSTM, excel at handling complex and non-linear time series data compared to traditional methods.

According to research that has been conducted, methods such as ARIMA have difficulty identifying long-term patterns and non-linear dependencies that are often found in mobility data. In this case, significant changes in September and other seasonal patterns make linear models such as ARIMA difficult to work well. LSTM models, on the other hand, are more effective at capturing these patterns thanks

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to their architecture, which can store information over long periods. This is evidenced by high accuracy rates on evaluation metrics such as RMSE and MAE. The unique contribution of this research lies in the integration of LSTM forecasting with K-Means segmentation in the specific context of the Jepara Bus Terminal. This combination not only provides passenger volume predictions but also categorizes operational periods, offering a more comprehensive dual insight for terminal management decision-making.

This model demonstrates good performance; however, it should be noted that external factors such as extreme weather conditions, major national holidays (e.g., Eid al-Fitr or Christmas), or special events (e.g., concerts or demonstrations) have not been integrated into the model. These factors can significantly affect passenger volume and potentially cause prediction inaccuracies if not taken into account. Therefore, future research could focus on incorporating these external factors as additional features to improve model accuracy. In addition, integration with real-time data from IoT sensors or tracking systems could enable more dynamic and responsive operational adjustments. This approach can also be expanded to analyze and predict mobility in other modes of transportation (e.g., trains, planes) or in more complex multimodal terminals, as well as explore other deep learning algorithms or more advanced hybrid architectures.

5. CONCLUSION

This model has shown promising results, but it's important to remember that it doesn't take into account things like extreme weather, major national holidays (like Eid al-Fitr or Christmas), or special events (like concerts or protests). If these factors are not taken into account, they can have a significant effect on the number of passengers and make predictions less accurate. So, future research could look into adding these outside factors as new features to make the model more accurate. Also, connecting to real-time data from IoT sensors or tracking systems could make it possible to make operational changes that are more flexible and responsive. This method can also be used to look at and predict how people will move in other types of transportation, like trains and planes, or in more complicated multimodal terminals. It can also be used to look into other deep learning algorithms or more advanced hybrid architectures.

REFERENCES

[1] A. M. Yasin and S. Yuliani, "Kajian Strategi Desain Terminal Bus Berkelanjutan Studi Kasus Terminal Induk di Kota Bekasi," *Ilmiah Arsitektur dan Lingkungan Binaan (ARSITEKTURA)*, vol. 22, no. 1, pp. 25–36, 2024, doi: 10.20961/arst.v22i1.81401.

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

[2] C. Filippi, G. Guastaroba, L. Peirano, and M. G. Speranza, "Trends in passenger transport optimisation," *International Transactions in Operational Research*, vol. 30, no. 6, pp. 3057–3086, 2023, doi: 10.1111/itor.13300.

[3] K. Steiner and S. Irnich, "Strategic planning for integrated mobility-on-demand and urban public bus networks," *Transportation Science*, vol. 54, no. 6, pp. 1616–1639, 2020, doi: 10.1287/trsc.2020.0987.

[4] A. Abdelwahed, P. L. van den Berg, T. Brandt, and W. Ketter, "Balancing convenience and sustainability in public transport through dynamic transit bus networks," *Transp Res Part C Emerg Technol*, vol. 151, p. 104100, 2023, doi: 10.1016/j.trc.2023.104100.

[5] Q. Sun, S. Chien, D. Hu, G. Chen, and R. Sen Jiang, "Optimizing Multi-Terminal Customized Bus Service with Mixed Fleet," *IEEE Access*, vol. 8, pp. 156456–156469, 2020, doi: 10.1109/ACCESS.2020.3018883.

[6] L. Monje, R. A. Carrasco, C. Rosado, and M. Sánchez-Montañés, "Deep Learning XAI for Bus Passenger Forecasting: A Use Case in Spain," *Mathematics*, vol. 10, no. 9, p. 1428, 2022, doi: 10.3390/math10091428.

[7] L. H. Tamiyati, "Redesain Terminal Tipe A Poris Plawad di Kota Tangerang dengan Tema Arsitektur Hijau" *Jurnal Arsitektur WASTUPADMA*, vol. 1, no. 1, pp. 010–022, 2023, doi: 10.62024/jawp.v1i1.2.

[8] M. Ariyanto, Zulkifli, Hamirul, Darmawanto, and Tarjo, "Manajemen Pelayanan Penumpang Di Terminal Bus," *Akuntansi Manajemen,Bisnis, dan Teknologi (AMBITEK)*, vol. 2, no. 1, pp. 41–58, 2022, doi: 10.56870/ambitek.v2i1.34.

[9] V. Shetty, S. Shinde, A. Sawant, and A. A. Kokate, "Smart Commute Application for Public Transport Management," *Interantional Journal of Scientific Research in Engineering and Management*, vol. 08, no. 05, pp. 1–5, 2024, doi: 10.55041/IJSREM35110.

[10] M. Davi and E. Winarko, "Rancang Bangun Aplikasi Peramalan Jumlah Penumpang Menggunakan Long Short-Term Memory (LSTM)," *Infotekmesin*, vol. 14, no. 2, pp. 303–310, 2023, doi: 10.35970/infotekmesin.v14i2.1911.

[11] P. Martí, A. Ibáñez, V. Julian, P. Novais, and J. Jordán, "Bus Ridership Prediction and Scenario Analysis through ML and Multi-Agent Simulations," *ADCAIJ: Advances in Distributed Computing and Artificial Intelligence Journal*, vol. 13, pp. e31866–e31866, 2024, doi: 10.14201/adcaij.31866.

[12] Prof. Gade S. A, Prof. Pandit R.B, Kalpesh Pawara, Tanveer Pinjari, Girish Patil, and Prakash Datir, "Real-Time Tracking System for City Bus Location and Passenger Count," *International Journal of Advanced Research in Science, Communication and Technology*, vol. 4, no. 2, pp. 295–302, 2024, doi: 10.48175/IJARSCT-22155.

[13] S. Inzudheen, J. Paul Mulerikkal, M. Jojee John, M. K, and G. M. Beveira, "Short-Term Passenger Count Prediction for Metro Stations using LSTM Network," *Journal of Computer and Mathematics Education*, vol. 12, no. 3, pp. 4026–4034, 2021, doi: 10.17762/TURCOMAT.V12I3.1693.
[14] Q. Ouyang, Y. Lv, J. Ma, and J. Li, "An LSTM-based method considering history and real-time data for passenger flow prediction," *Applied Sciences (Switzerland)*, vol. 10, no. 11, p. 3738, 2020, doi: 10.3390/app10113788.
[15] M. Nitti, F. Pinna, L. Pintor, V. Pilloni, and B. Barabino, "Iabacus: A Wi-Fi-based automatic bus passenger counting system," *Energies (Basel)*, vol. 13, no. 6, p. 1446, 2020, doi: 10.3390/en13061446.
[16] J. Jiang, C. Peng, W. Liu, S. Liu, Z. Luo, and N. Chen, "Environmental Prediction in Cold Chain Transportation of Agricultural Products Based on K-Means++ and LSTM Neural Network," *Processes*, vol. 11, no. 3, p. 766, 2023, doi: 10.3390/pr11030776.
[17] D. R. Sanjaya, B. Surarso, and T. Tarno, "Stock Price Forecasting on Time Series Data Using the Long Short-Term Memory (LSTM) Model," *International Journal of Current Science Research and Review*, vol. 07, no. 12, pp. 8866–8875, 2024, doi: 10.47191/ijcsrr/V7-i12-26.
[18] K. Yu, "Adaptive Bi-Directional LSTM Short-Term Load Forecasting with Improved Attention Mechanisms," *Energies (Basel)*, vol. 17, no. 15, p. 3709, 2024, doi: 10.3390/en17153709.
[19] M. Ding, Z. Wang, X. Zhou, and K. Wang, "Study of the Load Forecasting based on AKDC and LSTM algorithms," *J Phys Conf Ser*, vol. 2589, no. 1, p. 012035, 2023, doi: doi:10.1088/1742-6596/2589/1/012035.
[20] J. Xu, J. Gong, L. Wang, and Y. Li, "Integrating k-means Clustering and LSTM for Enhanced Ship Heading Prediction in Oblique Stern Wave," *J Mar Sci Eng*, vol. 11, no. 11, p. 2185, 2023, doi: 10.3390/jmse11112185.
[21] L. Wang, S. Mao, B. M. Wilamowski, and R. M. Nelms, "Ensemble Learning for Load Forecasting," *IEEE Transactions on Green Communications and Networking*, vol. 4, no. 2, pp. 616–628, 2020, doi: 10.1109/TGCN.2020.2987304.
[22] G. K, M. S, S. Logavaseekarapakther, P. A, and M. Farook R, "Enhanced Unsupervised K-Means Clustering Algorithm," *ShodhKosh: Journal of Visual and Performing Arts*, vol. 5, no. 1, pp. 1141–1150, 2024, doi: 10.29121/shodhkosh.v5.i1.2024.2867.
[23] K. D. Hartomo and Y. Nataliani, "A New Model for Learning-based forecasting Procedure by Combining k-means Clustering and Time Series forecasting Algorithms," *PeerJ Comput Sci*, vol. 7, p. e534, 2021, doi: 10.7717/PEERJ-CS.534.
[24] M. A. Mohammed, M. M. Akawee, Z. H. Saleh, R. A. Hasan, A. H. Ali, and T. Sutikno, "The effectiveness of big data classification control based on principal component analysis," *Bulletin of Electrical Engineering and Informatics*, vol. 12, no. 1, pp. 427–434, 2023, doi: 10.11591/eei.v12i1.4405.

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

[25] B. M. S. Hasan and A. M. Abdulazeez, "A Review of Principal Component Analysis Algorithm for Dimensionality Reduction," *Journal of Soft Computing and Data Mining*, vol. 2, no. 1, pp. 20–30, 2021, doi: 10.30880/jscdm.2021.02.01.003.

[26] S. D. Axen, M. Baran, R. Bergmann, and K. Rzecki, "Manifolds.jl: An Extensible Julia Framework for Data Analysis on Manifolds," *ACM Transactions on Mathematical Software*, vol. 49, no. 4, pp. 1–3, 2023, doi: 10.1145/3618296.

[27] T. S. Sushanth, T. S. Siddarda, A. Sathvika, A. Shruthi, A. S. Lekha, and T. Kumar, "Time Series Forecasting using RNN," *Interantional Journal of Scientific Research in Engineering and Management*, vol. 08, no. 11, pp. 1–8, 2024, doi: 10.55041/IJSREM39164.

[28] S. M. Al-Selwi, M. F. Hassan, S. J. Abdulkadir, and A. Muneer, "LSTM Inefficiency in Long-Term Dependencies Regression Problems," *Journal of Advanced Research in Applied Sciences and Engineering Technology*, vol. 30, no. 3, pp. 16–31, 2023, doi: 10.37934/araset.30.3.1631.

[29] G. Li *et al.*, "Towards smart transportation system: A case study on the rebalancing problem of bike sharing system based on reinforcement learning," *Journal of Organizational and End User Computing*, vol. 33, no. 3, pp. 35–49, 2021, doi: 10.4018/JOEUC.20210501.oa3.

[30] S. Murrar, F. Alhaj, and M. H. Qutqut, "Machine Learning Algorithms for Transportation Mode Prediction: A Comparative Analysis," *Informatica*, vol. 48, no. 6, pp. 117–130, 2024, doi: 10.31449/INF.V48I6.5234.