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Predicting Transjakarta Passengers with LSTM-BiLSTM Deep Learning Models for Smart Transportpreneurship

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ABSTRACT

Travel pattern variations pose challenges in building a prediction model that accurately captures seasonal patterns or precision of BRT passenger numbers. **An approach** that integrates sophisticated prediction algorithms with high accuracy is needed to address the Transjakarta BRT passenger number prediction model problem. The proposed prediction model with the best accuracy is sought using deep learning on 8 models. The prediction model is used for short-term and long-term predictions, as well as looking for correlations in the prediction results of 13 Transjakarta corridors. The Python programming language with the Deep Learning Tensor Flow framework is run by Google Colaboratory used in the prediction simulation environment. **The combination** of BiLSTM-CNN was found to have the best accuracy of the evaluation value (SMAPE = 15.9387, MAPE = 0.598, and MSLE = 0.0425), although it has the longest time (134 seconds). **Fluctuations** in short-term predictions of passenger numbers evenly occur simultaneously across all corridors. Fluctuations in long-term predictions evenly occur simultaneously across all corridors, except in February. There is no negative correlation in the 13 prediction results and there are 8 corridors that have a close positive correlation. **The prediction** results can be used by transportation operators and the government to optimize resource planning and transportation policies to support sustainable community and economic mobility.

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1. INTRODUCTION

Road public transport passengers continue to increase along with increasingly complex mobility needs [1, 2] amidst increasing urbanization and population growth [3, 4]. The social, economic, and demographic diversity of society can be seen from road public transport passengers [5]. Road public transport can continue to play a role as the backbone of mobility, supporting economic growth [6, 7], and the quality of life of its passengers in agglomeration areas [8]. Road public transport passengers need accessibility to various destinations such as workplaces, schools, markets, or shopping centers [9]. The challenges of comfort, safety, and punctuality are often the main concerns for passengers [10]. The behavior and habits of road public transport passengers are important factors in creating a harmonious road transport system [1, 9]. External factors such as road infrastructure conditions, traffic congestion, and operational management of transport affect the passenger experience [5, 6]. A deep understanding of the needs and behavior of public transport passengers is very important in designing a more effective and sustainable road public transport system [11, 12]. Road transport passengers are a central element in the public transport system that reflects the diversity of mobility needs of the community [13]. Bus Rapid Transit (BRT) passengers who come from various social and economic groups are an important indicator in measuring the sustainability of the road public transport system as part of a strategic economic infrastructure [14, 15]. BRT passengers come from various backgrounds such as office workers, students, and the general public who prioritize speed, punctuality, and comfort [16, 17]. Relatively affordable fares make BRT an inclusive transportation alternative, especially for lower-middle class communities [18, 19]. The existence of BRT encourages local economic growth through increased commercial activity around BRT stops or corridors [20, 21]. The challenges of BRT in meeting the needs of its passengers are passenger density, limited fleet, and integration between other modes of transport [22, 23]. The success of BRT in attracting passengers is highly dependent on factors such as comfort, safety, and reliability of the services offered [24, 25]. Understanding the needs and preferences of BRT passengers is very important to ensure the sustainability of the road public transportation system [26, 27]. BRT as a mode of road public transportation that can accommodate a large number of passengers is the main catalyst for sustainable economic development to overcome mobility challenges in urban areas [28].

Various passenger flow prediction techniques are conducted by identifying key parameters to overcome the challenges of road public transport in urban areas [29]. The TSD-ST (Time Series Decomposition-Spatiotemporal) model provides an average accuracy improvement of 21.87% in predicting multi-station bus public transport passenger flow compared to previous methods [30]. A realistic MATSim (Multi-agent, Activity-based, Travel demand Simulator) based BRT travel demand prediction model in Dhaka is significantly affected by sensitivity to travel time, cost, and multimodal access [31]. The Artificial Neural Network(ANN) model shows higher travel time prediction accuracy compared to the regression model, especially on BRT routes without signalized intersections [32]. The DAMSCN (Dual Attention Multi-Scale Convolutional Network) model is used to predict short-term origin-destination Xiamen BRT (XMBRT) and Shanghai Metro (SHMetro) with improved prediction accuracy and stability compared to the best baseline with significant reduction in MAE and RMSE [33]. Deep Sailfish Network (DSFN) for passenger prediction and fuzzy logic for route changes were used in the prediction model of four BRT routes from Gujarat India which proved superior accuracy based on MAPE and RMSE metrics [34]. The Multitask Deep Learning-Service level Passenger Flow Prediction(MDL-SPFP) model with ARM network resulted in bus passenger flow prediction with 22.39% accuracy improvement compared to the best baseline [35]. The best prediction model for Transjakarta BRT passenger number was obtained from the combination of BiLSTM-CNN with high accuracy at the lowest MSLE, MAPE, and SMAPE values, although it required longer computation time [36]. The deep learning approach was used for the prediction model with greedy layer-wise algorithm, LSTM, and RNN to process cluster data, eliminate redundancy, and produce accurate passenger flow prediction and revenue estimation in Karnataka State Road Transport Corporation Bus Rapid Transit (KSRTCBRT) [37].

Variations in travel patterns pose challenges in building predictive models that can accurately capture seasonal patterns or short-term fluctuations [38]. Passenger data is affected by inaccurate recording, lack of integration of electronic ticketing systems with operational data, or limited historical data that can reduce the reliability of predictive models [39]. Predictive models often have difficulty accommodating factors that are unpredictable or difficult to measure [40]. The complexity of variables often involved in predictive models affects the risk of overfitting the training data [41]. Unbalanced data distribution makes predictive models less effective in estimating the number of passengers on a particular route due to bias towards routes with dominant data [42]. Models that are too complex or require a lot of computing resources become impractical to implement in a BRT operational environment [32]. Predictive models that are not built based on historical data have difficulty adapting quickly to changes that occur [43–45]. An approach that integrates sophisticated prediction algorithms with high accuracy using high-quality and real-time data is needed to overcome the problems of BRT passenger prediction models [46]. Long and short term predictions of Transjakarta BRT passenger numbers are essential to improve operational efficiency and optimize the expenditure of available resources [36, 47–50]. High accuracy prediction is needed by Transjakarta BRT for the mission of minimizing operational costs, maximizing revenue, reducing social costs, and increasing economic productivity. The search for the best accuracy prediction model is proposed using the deep learning approach of LSTM and BiLSTM models with a combination of CNN, GRU, and Transformer evaluated by MAPE, SMAPE, and MSLE. Comparison of the lowest value of the 3 evaluation matrices and the time required is the basis for selecting the best prediction model. Short-term predictions (the next 30 days) and long-term predictions (the next 12 months) of the number of passengers and the strong correlation of the Transjakarta BRT corridor are carried out by the best prediction model. This prediction model has never been done in the field of road public transportation and has become a necessity for Transjakarta BRT. The prediction results can be used to create a road public transportation system that is more efficient, sustainable, and responsive to passenger needs. The prediction results of the number of Transjakarta BRT passengers can be used to support infrastructure planning, transportation policy decision making, and improve service quality.

2. RESEARCH METHOD

The CSV dataset was collected with the contents of the date and number of passengers for each private Transjakarta BRT corridor. Transjakarta BRT was taken as a case study because the center of BRT transportation system development is in the largest urban agglomeration area with the highest complexity in Indonesia. The Python programming language with the Tensor Flow deep learning framework was run by Google Colaboratory on the macOS Venture 13.5 Operating System and 8 GB of RAM was used in the prediction simulation environment. Minmax feature scaling was used for initial data processing which was then divided into two segments (training and testing). The LSTM, LSTM-CNN, LSTM-GRU, LSTM-Transformers, BiLSTM, BiLSTM-CNN, BiLSTM-GRU, BiLSTM-Transformers models were run to find the best prediction model based on the best accuracy value given by 3 evaluation matrices (MSLE, MAPE, and SMAPE). The lowest evaluation value from the experiment became the best model. The prediction model architecture produces the best prediction model for predicting short-term (next 30 days) and long-term (next 12 months) passenger numbers, as well as Transjakarta BRT corridor relationships in Figure 1.

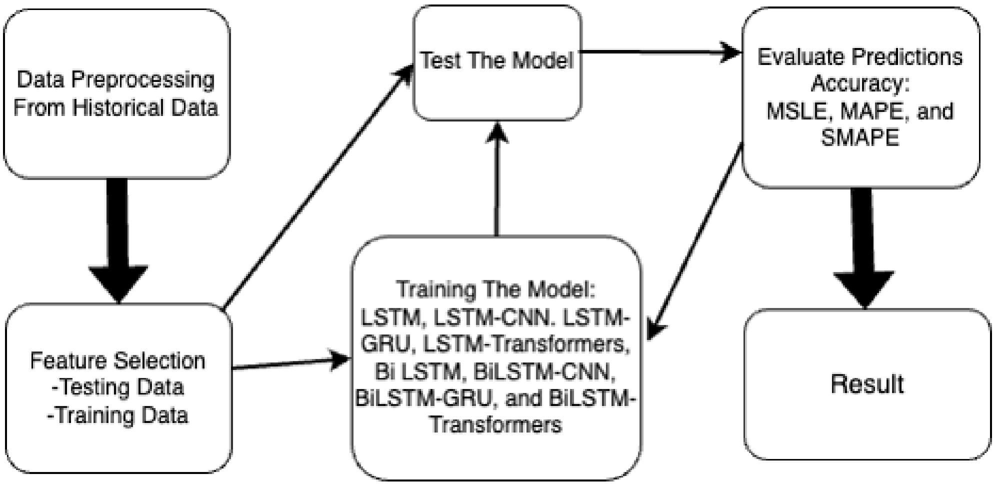

Figure 1. Prediction Model Architecture

Long Short-Term Memory (LSTM) and Bidirectional Long Short-Term Memory (BiLSTM) are variants of Recurrent Neural Networks (RNN) designed to process sequence data such as text, speech signals, and time-series data [51–54]. LSTM is designed to process and make predictions based on time-series data [55–57]. LSTM processes sequential data by receiving the current input (x_t) and the previous hidden output (h_{t-1}). The forget gate determines the information to be forgotten, while the input gate adds new information to the cell memory [58–60]. The output gate produces the hidden output (h_t). The output gate produces the hidden output (h_t) passed to the next step which allows LSTM to capture long-term and short-term relationships effectively [61, 62]. BiLSTM processes sequential data in two directions (forward and backward) combining information from the past and future to produce a richer representation at each time step [36, 54, 63]. A BiLSTM unit generates two hidden states, one from the forward LSTM (h_t) and one from the backward LSTM ($\overline{h_t}$) at each time step t. The two hidden states are combined to produce the final representation ($\hat{h_t} = [h_t, \overline{h_t}]$) [64, 65]

The consistency and speed of the proposed prediction model performance are seen from 3 types of evaluation matrices, namely MSLE, MAPE, and SMAPE. Mean Squared Logarithmic Error (MSLE) measures the error between the predicted value and the actual value by comparing the logarithm of both to emphasize relatively smaller errors and reduce the impact of outliers. MSLE measures the average of the logarithm of the squared error between the predicted and actual values [66] (Equation 1). Mean Absolute Percentage Error (MAPE) measures the prediction error by calculating the average of the absolute percentage error between the predicted value and the actual value to provide a proportional picture of the model accuracy. MAPE divides each error based on its respective request [67] (Equation 2). Symmetric Mean Absolute Percentage Error (SMAPE) measures the prediction error by calculating the average of the normalized absolute percentage error using the average of the predicted value and the actual value to ensure symmetry. SMAPE is a percentage and is not scale-dependent, so it can be used to evaluate the prediction performance of time series data sets [68] (Equation 3). SMAPE values that are increasingly close to 0 indicate increasingly better model performance [55].

$$\text{MSLE} = \frac{1}{n}\sum_{i=1}^{n}\big(\log(y_i+1) - \log(\hat{y}_i+1)\big)^2, \tag{1}$$

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{\hat{y}_i - y_i}{y_i}\right|, \tag{2}$$

$$\text{SMAPE} = \frac{1}{n}\sum_{i=1}^{n}\frac{|\hat{y}_i - y_i|}{|y_i| + |\hat{y}_i|}. \tag{3}$$

3. RESULT AND DISCUSSION

The historical dataset contains the daily number of passengers for each Transjakarta BRT corridor, recorded from January 1, 2021, to December 31, 2023. The preprocessed data is provided in a Comma-Separated Values (CSV) file with 1,095 entries. The dataset consists of 14 columns: DATE, representing the date, and K1–K13, which contain the number of passengers for each corridor (1–13) of the Transjakarta BRT. See Figure 2.

	DATE	K1	K2	K3	K4	K5	K6	K7	K8	K9	K10	K11	K12	K13
0	2021-01-01	13466	6037	7834	3726	6380	3516	6925	7635	9179	6249	2390	1887	3641
1	2021-01-02	18197	7848	10889	5548	10629	5518	9850	10052	13188	8333	3484	2905	5798
2	2021-01-03	16317	7561	10071	4509	9265	4690	10847	9255	11385	7472	3084	2297	5217
3	2021-01-04	31360	13095	17883	10059	15552	13625	16061	16628	25613	14144	5616	5464	11164
4	2021-01-05	30103	12305	16029	9939	14781	13496	14072	15511	24678	13741	5136	5336	10543
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
1090	2023-12-27	58937	33194	26783	19607	27049	31440	24125	30965	48740	21976	8600	10095	35170
1091	2023-12-28	61410	33179	26683	19387	27382	30448	23541	31227	48590	21961	8334	10435	34946
1092	2023-12-29	58457	32286	25766	18098	26207	27172	22203	29714	45841	21536	8159	9723	33244
1093	2023-12-30	55027	27569	23431	13428	22838	20045	17739	23345	28059	16134	6872	9832	21947
1094	2023-12-31	43514	26273	21565	13164	19838	19763	16464	22239	24102	14004	6218	8811	20720

1095 rows × 14 columns

Note: K1=Corridor 1, K2=Corridor 2, K3=Corridor 3, K4=Corridor 4, K5=Corridor 5, K6=Corridor 6, K7=Corridor7, K8=Corridor 8, K9=Corridor 9, K10=Corridor 10, K11=Corridor 11, K12=Corridor 12, K13=Corridor 13.

Figure 2. Dataset

Minmax feature scaling divides 80% training data and 20% testing data. The prediction models used for the experiment are LSTM, LSTM-GRU, LSTM-CNN, LSTM-Transformers, BiLSTM, BiLSTM-GRU, BiLSTM-CNN, and BiLSTM-Transformers. Parameter settings for each prediction model with 2 hidden layers, activation hyperbolic tangent (tahn), dropout 0.20, epoch 60, batch size 16, verbose 1, and adam optimizer. These parameter provisions are proven to be the most appropriate for the LSTM model [36, 53, 54]. The most optimal accuracy value of the 3 evaluation matrices is BiLSTM-CNN (SMAPE = 15.9387, MAPE = 0.598, and MSLE = 0.0425). The BiLSTM model has a higher accuracy than LSTM. BiLSTM and LSTM combined with GRU, CNN, and Transformers are proven to improve accuracy. The best combination for BiLSTM and LSTM is with CNN which produces the best accuracy value compared to GRU and Transformers (Figure 3). The power of BiLSTM is able to capture richer temporal relationships by utilizing information from both directions (forward and backward) compared to LSTM which only works in one direction [36, 69]. The combination becomes more optimal with the addition of CNN which is able to capture spatial features or local patterns in the data, strengthening the feature representation before the classification or prediction process. Each model has a specific role in strengthening the generalization ability of the main model, but CNN has proven to be the best match because of its strong ability to extract features from sequential data, resulting in better accuracy values compared to combinations with GRU or Transformers. The hybrid approach by combining the power of BiLSTM to process long-term dependencies with the ability of CNN to capture local patterns is an effective strategy to maximize accuracy.

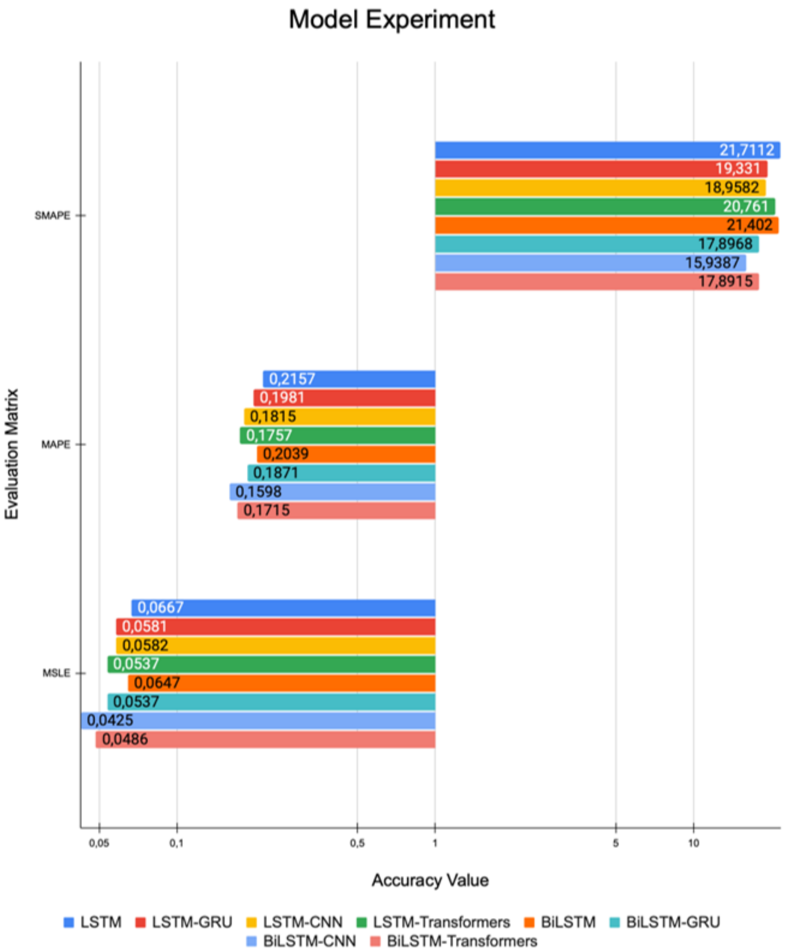

Figure 3. Prediction Model Experiment

The fastest prediction time model is owned by the LSTM model (31 seconds), but the evaluation value of the 3 evaluation matrices is still high compared to other prediction models. The longest time is BiLSTM-CNN (134 seconds), but the evaluation value of the 3 evaluation matrices is the lowest compared to the others (Figure 4). The high speed of LSTM is due to its architecture which only processes data in one direction, thus reducing computational complexity [59]. The one-way approach does not sufficiently capture more complex temporal relationships in the data, resulting in a still high evaluation value. The long computation time of the BiLSTM-CNN combination can be explained by the nature of BiLSTM which processes data in two directions (forward and backward) and the addition of CNN which adds a layer of feature processing. This combination allows the model to capture temporal and spatial patterns in more depth and produce more accurate prediction performance, although it requires more computational time. These results indicate a trade-off between speed and accuracy in model selection. LSTM is suitable for use if prediction speed is a priority such as real-time applications. BiLSTM-CNN is more ideal for high accuracy which is preferred, although it requires longer computation time. Model selection should consider the specific needs of the application to be applied.

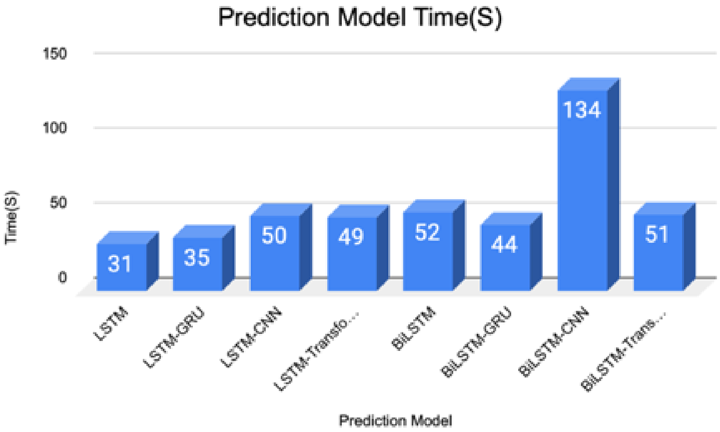

Figure 4. Prediction Model Time

The proposed deep learning approach prediction model with a combination of BiLSTM-CNN performs short-term (30 days later) and long-term (12 months later) predictions of the number of passengers on 13 Transjakarta BRT corridors at the same time. The prediction of the number of passengers for the next 30 days is consistently the highest in corridor 1, while the lowest is in corridor 11. Fluctuations in the number of daily passengers evenly occur simultaneously in all corridors. The number of passengers at the beginning of the month increases and decreases quite sharply, but tends to be stable at the end of the month. Several corridors intersect from the beginning of the month to the end of the month in corridors 3, 5, 6, 7, 8, 9, 10, 12, and 13. See in Figure 5).

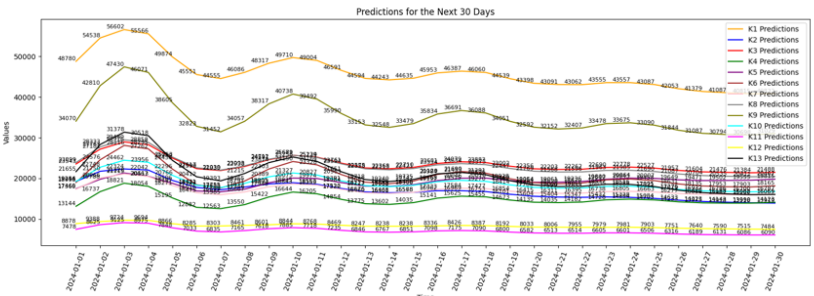

Figure 5. Predictions For The Next 30 Days

Corridor 1 has the highest number of passengers over 30 days, indicating high demand on the route. This may indicate that the corridor serves areas with high economic activity, such as business centers, markets, or industrial areas. Transportation managers can focus on increasing service capacity in this corridor, such as increasing the number of fleets, improving infrastructure, or increasing the frequency of departures to accommodate user needs [15]. The consistently low number of passengers in corridor 11 may reflect a lower level of economic activity in the area. This opens up opportunities for further study of the low number of passengers which may be caused by lack of accessibility, lack of promotion of transportation services, or minimal economic activity in the area. Development efforts such as improving connectivity or encouraging investment in this area can help increase the use of transportation services and economic activity [16].

Fluctuations in the number of passengers that occur evenly across the corridor reflect uniform travel patterns that can be influenced by the daily cycle of community activities such as work, school, or other routine activities. Sharp increases and decreases at the beginning of the month indicate the influence of the monthly economic cycle, such as salary receipts or community spending patterns. This understanding can be used to set promotional or incentive strategies, such as fare discounts or adding fleets at certain times to maximize revenue. The number of passengers that tends to be stable at the end of the month indicates a more predictable travel pattern. This provides an opportunity for transportation operators to optimize resource management, such as more efficient travel schedules and more even fleet distribution [17]. Several intersecting corridors reflect high interconnections between regions. This shows the importance of coordinated management to ensure smooth passenger movement in these corridors. Strategies such as schedule integration, adding connecting routes, or implementing integrated fares can improve passenger comfort and the efficiency of the transportation system. The prediction of the number of passengers for the next 12 months is consistently the highest in corridor 1, while the lowest is in corridor 12 which is adjacent to corridor 11. Fluctuations in the number of monthly passengers evenly occur simultaneously in all corridors, except in February where 12 corridors experienced an increase and 1 corridor experienced a decrease (Corridor 5). The number of passengers from February to December tends to be stable. There are no overlapping corridors in all months. See in Figure 6.

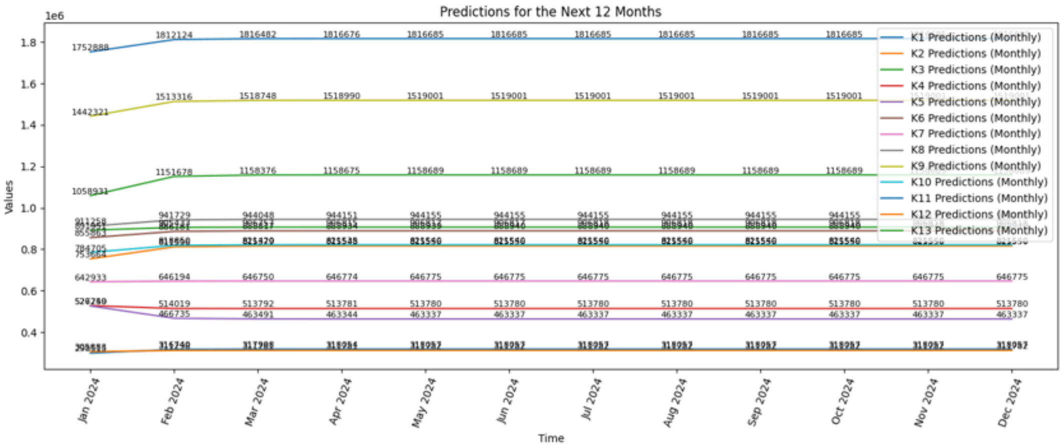

Figure 6. Predictions For The Next 12 Months

Corridor 1 remains the busiest over the 12 months, indicating that the corridor serves an area of high economic activity, such as a central business district, commercial district, or high-density population. This consistency underscores the importance of the corridor as the backbone of the transportation system. Infrastructure and service investments are needed to support economic efficiency, such as the acquisition of additional fleets, increased service schedules, or improvements to supporting facilities [18]. Corridor 12, which has the lowest ridership and is close to corridor 11, suggests that there may be limited economic activity in the area. This may also reflect limited accessibility or lack of transportation integration. Governments or transportation operators may want to evaluate the potential for development in the area, such as improving connectivity to areas with higher economic activity or encouraging local economic growth through infrastructure investment [19]. The consistent monthly ridership fluctuations across the corridors reflect a uniform seasonal pattern that is likely influenced by economic cycles, weather, or community habits. The anomaly in February where 12 corridors experienced an increase while Corridor 5 experienced a decrease could be caused by specific factors, such as changes in travel patterns, rerouting, or certain events affecting the Corridor 5 area. A more in-depth evaluation is needed to understand these factors and optimize services in Corridor 5 during the month. The number of passengers that tended to be stable from February to December indicates the consistency of transportation demand. This stability provides advantages for transportation operators in planning resources, including fleet distribution, travel schedules, and operational budget allocations. This stability allows for more efficient planning to support the sustainability of public transportation services [21, 22]. The absence of overlapping corridors indicates that each corridor serves a unique and separate route. This can indicate the clarity of the market segment or area served by each corridor. Opportunities to improve integration between corridors can be explored to drive transportation efficiency and improve passenger mobility across regions.

Correlation Network Graph is used to present close correlation (positive blue line and negative red line) in the prediction results of 13 Transjakarta BRT corridors. There is no negative correlation in the 13 prediction results, while there are 8 corridors that have close positive correlation (Corridor 3, Corridor 6, Corridor 7, Corridor 8, Corridor 9, Corridor 10, Corridor 11, and Corridor 13), the rest have positive but not close correlation. The most close positive correlations are in corridor 8 and corridor 10 as many as 5 correlations. Corridor 8 has a close positive correlation with Corridor 3, Corridor 11, Corridor 10, Corridor 9, and Corridor 13. Corridor 10 has a close positive correlation with Corridor 3, Corridor 11, Corridor 8, Corridor 9, and Corridor 6. The least close positive correlation only has 1 relationship, namely in corridor 7 with corridor 3 see in Figure 7.

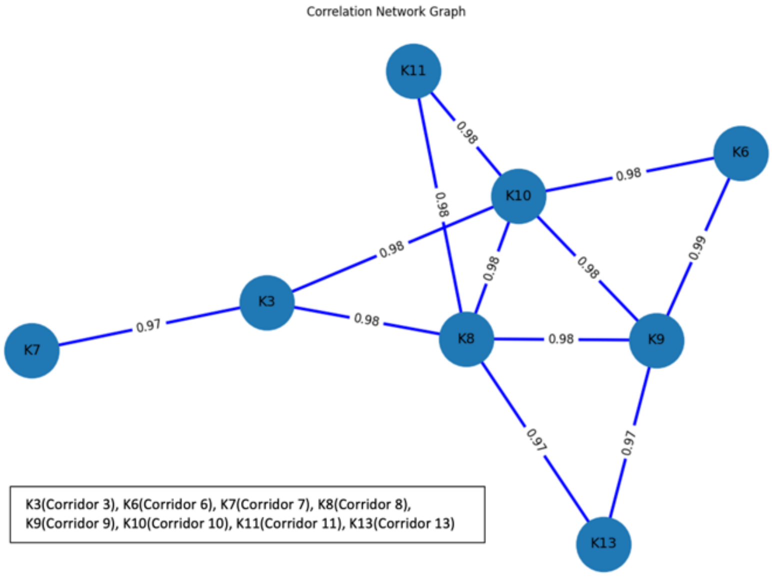

Figure 7. Prediction Correlation Heatmap

The absence of negative correlations between the predicted number of passengers on the 13 corridors indicates that the movement of the number of passengers in each corridor is mutually supportive. An increase or decrease in the number of passengers in one corridor tends not to hinder activity in other corridors. This reflects a well-integrated transportation system in each corridor serving complementary, not competing, needs. The 8 corridors with close positive correlations indicate that the areas served by the corridors have strong economic relationships. These corridors may connect areas with mutually supportive economic activities, such as business districts, housing, or shopping centers. Management can focus on improving connectivity and efficiency in these corridors to provide significant economic impacts [24, 26]. Strong relationships reflect important passenger flows to support economic activities. Corridors 8 and Corridor 10 have the highest number of close positive correlations (5 correlations), indicating that these corridors are strategic routes that play an important role in connecting various regions. Corridor 8 serves areas with diverse and strategic economic activities, while Corridor 10 shows a central role in supporting mobility in the connected areas. Investments in Corridor 8 and Corridor 10 provide broader economic benefits due to their correlation with other regions, such as infrastructure, fleet, and supporting facilities. Other corridors with positive but weak correlations reflect weak or specific economic relationships between regions. Corridor 7 and Corridor 3 correlations indicate that the influence between regions is not very significant. This provides an opportunity to evaluate whether connectivity in these corridors can be improved or whether the areas served need additional economic support to strengthen relationships [41]. These results can be used to direct transportation and economic strategies by focusing on corridors with strong correlations, encouraging investment in areas with strong positive correlation corridors, maximizing economic synergies between regions, and strategic interventions to improve economic integration and mobility.

The BiLSTM-CNN prediction model produces short-term predictions, long-term predictions, and correlations of prediction results. The short-term prediction results can be used to improve the efficiency of public transportation services, support economic growth in strategic areas, and reduce inequality in access between regions. Transportation operators and governments can use the results to optimize resource planning and short-term transportation policies to support sustainable community mobility [42]. The long-term prediction results show the importance of segmented and data-based transportation management. Corridors with high demand (Corridor 1) require adequate infrastructure support to maintain efficiency and comfort. Corridors with low demand (Corridor 12) require strategic interventions to encourage their use, including regional development and connectivity. Analysis of monthly fluctuations and long-term stability provides opportunities for operational optimization and sustainable service plannin [46]. The strong positive correlation between BRT corridors indicates the potential for strong economic ties in the areas served. Focusing on improving services in strategic corridors can have broad economic impacts [13]. Further analysis of corridors with limited correlation can help identify opportunities to improve connectivity and synergies between regions. This allows the transportation system to be more efficient and supports sustainable economic growth.

4. MANAGERIAL IMPLICATIONS

The findings of this study provide valuable insights for improving the management and efficiency of the Transjakarta BRT system. The predictive model helps transportation operators allocate resources effectively by identifying high-demand corridors that require increased service capacity and optimizing fleet distribution.

Additionally, accurate passenger forecasts enable better planning for infrastructure investment, ensuring that public transport remains reliable and efficient. Policymakers can use these insights to enhance connectivity between corridors, improve service quality, and develop sustainable urban mobility strategies.

By leveraging data-driven decision-making, Transjakarta can optimize operations, reduce costs, and enhance the overall passenger experience while supporting economic growth in key areas.

5. CONCLUSION

This study evaluates eight deep learning-based prediction models for forecasting Transjakarta BRT passenger numbers, with the BiLSTM-CNN model demonstrating the highest accuracy. Although this model requires the longest computation time, it effectively predicts both short-term and long-term passenger trends while identifying correlations across 13 Transjakarta corridors. The findings indicate that Corridor 1 consistently has the highest passenger count, while Corridor 12 has the lowest, with demand fluctuations occurring uniformly across most corridors except in February. Additionally, eight corridors exhibit strong positive correlations, indicating interconnectivity in passenger movement.

These results provide valuable insights for optimizing fleet management, improving service efficiency, and informing data-driven transportation policies. By leveraging predictive analytics, operators and policymakers can enhance the planning of public transportation services, ensuring better resource distribution and connectivity across Jakarta's transit network.

For future research, integrating additional external factors such as weather conditions, economic fluctuations, and policy changes could refine prediction accuracy. Furthermore, incorporating Origin-Destination (OD) modeling would offer deeper insights into passenger movement, enabling more precise adjustments to service distribution and reducing congestion at key transit points. Expanding this model to cover intermodal transportation, including MRT and LRT, could further enhance its applicability in urban mobility planning.

6. DECLARATIONS

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6.2. Author Contributions

Conceptualization: JS and IS; Methodology: HH; Software: EA; Validation: UR; Formal Analysis: JS, UR, and EA; Investigation: IS; Resources: HH; Data Curation: IS; Writing Original Draft Preparation: JS and IS; Writing Review and Editing: UR, EA, and HH; Visualization: EA; All authors, JS, HH, UR, IS, and EA have read and agreed to the published version of the manuscript.

6.3. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

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The authors received no financial support for the research, authorship, and/or publication of this article.

6.5. Declaration of Conflicting Interest

The authors declare that they have no conflicts of interest, known competing financial interests, or personal relationships that could have influenced the work reported in this paper.

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