INTERNATIONAL SCIENTIFIC JOURNAL OF ENGINEERING AND MANAGEMENT (ISJEM) ISSN: 2583-6129
VOLUME: 04 ISSUE: 04 | APRIL – 2025 DOI: 10.55041/ISJEM02634
AN INTERNATIONAL SCHOLARLY || MULTIDISCIPLINARY || OPEN ACCESS || INDEXING IN ALL MAJOR DATABASE & METADATA

A Deep Learning Approach To Comparative Sentiment Analysis For Ride-Hailing Apps

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***Abstract* — The swift growth of ride-hailing services in urban transportation has transformed the mobility landscape, necessitating that providers grasp customer sentiment to enhance their offerings. This research conducts a comparative sentiment analysis of user feedback for Ola, Uber, Rapido, and Namma Yatri, with the objective of deriving significant insights regarding customer satisfaction and service quality. A comprehensive dataset comprising 40,000 reviews from the Google Play Store for each application was gathered and classified into positive, neutral, and negative sentiments. To analyze sentiment trends, both advanced deep learning models (including LSTM, GRU, and Hybrid LSTM-CNN) and traditional machine learning models (such as Random Forest and Decision Tree) were utilized. The results show that even though the Random Forest model had the highest accuracy among the traditional methods, the Hybrid LSTM-CNN model was the best among all, reflecting the power of deep learning architectures in identifying complex sentiment patterns. The findings obtained from this study gave significant recommendations for ride-hailing companies to boost their customers' satisfaction levels and streamline business processes.**

Keywords — Sentiment Analysis, Ola, Uber, Rapido, Namma Yatri, Machine learning, Deep learning, LSTM, GRU, Hybrid LSTM-CNN

I. INTRODUCTION

Ride-hailing platforms have changed how people travel in cities, providing easy, affordable, and efficient mobility services. Ride-hailing services such as Uber, Ola, and other demand-based transportation providers have altered the dynamics of urban mobility. In the past, individuals used personal cars, taxis, or public transport to commute. However, the dramatic growth in these ride-hailing services has given rise to a more flexible, affordable, and efficient transportation network that serves millions around the world[1]. Ride-hailing has been on the rise in cities over the last several years, and dynamic ride-hailing platforms are serious contenders to traditional taxi services[2]. The swift growth of mobile technology has changed social media into a platform for people to express their thoughts and emotions. Public sentiment analysis is important to companies and political parties alike, as it can help them make strategic choices. In such a context, sentiment analysis plays a significant role in determining public opinion[3]. It is the way of studying textual information to determine its emotional tone, whether it is positive, negative, or neutral[4]. A positive sentiment indicates satisfaction, gratitude, or positive feelings, usually expressed by adjectives like "awesome" or "great". A negative sentiment indicates unhappiness, complaints, or bad experiences, with words such as "bad" or "terrible". A neutral sentiment indicates remarks that are factual or do not express strong emotions, such as "was okay" or "not bad".

Fig 1: Sentiment analysis categories

Fig. 1 provides a conceptual representation of sentiment categories: positive(green), neutral(yellow), and negative(red). These sentiments reflect users' satisfaction or dissatisfaction with various service aspects, such as pricing, driver behaviour, ride availability, and the app performance. Understanding these sentiments allows service providers to effectively enhance user experience and address recurring complaints.

The research aims to perform sentiment analysis on user reviews of major Indian ride-hailing applications such as Ola, Uber, Namma Yatri, and Rapido through conventional machine learning models as well as deep learning models. The aim is to categorize user sentiments as positive, neutral, or negative and compare various models' performances to identify the best method for sentiment classification.

Machine Learning(ML) is an area of Artificial Intelligence(AI) where machines employ data to find patterns and make decisions with the least amount of human intervention. The most vital feature of an ML model is that it should be able to learn on its own, train from past

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computations, and provide consistent results on repeated exposure to new datasets[5]. Deep Learning(DL), which is a subset of ML, makes it possible to learn from unstructured or unlabelled data by constructing representations from human brain knowledge. In contrast to conventional methods involving manual feature extraction, DL works directly with raw data to classify and identify patterns[6].

This study employs both ML and DL methods for sentiment analysis on users' reviews of popular Indian ride-hailing apps. Conventional ML models like Decision Tree(DT), Random Forest(RT), and deep learning models like Long Short-term Memory(LSTM), Gated Recurrent Unit(GRU), and hybrid models are employed for sentiment classification. The research not just measures model performance based on precision such as accuracy, F1-score, confusion matrix, and ROC curve, but also conducts sentiment comparison on trends between different ride-hailing apps, Comparing user attitudes, it offers useful implications for service quality, customer happiness, and optimization areas, to boost the overall performance of these apps in terms of users' experience.

II. LITERATURE SURVEY

Sentiment analysis has been performed using different ML and DL models on user-generated content, especially social media and app reviews. Different methods of sentiment analysis in ride-sharing apps have been studied in various research works. Naïve Bayes and Support Vector Machines(SVM) were applied because of their effectiveness in text classification. Anthal et al.[7] used SVM and Naïve Bayes for sentiment analysis of Ola and Uber tweets and achieved accuracies of 86.65% and 84.87%, respectively. Also, Wiguna et al. [8] compared Naïve Bayes with SVM on the Gojek app reviews and attained 90% accuracy for SVM and 77% for Naïve Bayes. Atina et al. [9], analysed the reviews of the Grap app using RF, SVM, and Naïve Bayes with 95.14% accuracy using RF. The study, however, was limited to Grab alone and lacked generalizability.

DL algorithms, such as Convolutional Neural Networks (CNN), Deep Feed Forward Neural Network (DFFNN), and Recurrent Neural Network (RNN), have been shown to outperform them. Satya et al.[10] have done sentiment analysis of Uber data based on CNN and DNN models with an accuracy of 96% using CNN and 96.3% using DNN. Ahammad et al. [11], also researched BiGRU and GRU models on the review of ride-sharing apps and found accuracies of 94.97% and 94.09%, respectively. Mahadevaswamy et al. [12]Compared the performance of deep learning models for sentiment analysis and concluded that Bidirectional LSTM (Bi-LSTM) performed better than other methods, with 91.4% accuracy. Rustam et al.[13], analysed sentiment classification with ML and DL models, with a focus on the significance of feature engineering in the enhancement of sentiment analysis accuracy, where Extra Trees Classifier(ETC) got the highest accuracy of 92%.

Most sentiment analysis studies rely on publicly available data, such as tweets and app store reviews. Becerra-Salas et al.[14], captured tweets covering 12 years to check customer opinion, whereas Ahammad et al.[11] utilized 12,052 app reviews in Google Play. Despite the availability of large datasets, challenges such as data imbalance, noise in user reviews, and limited labelled data hinder sentiment analysis accuracy.

In this study, we performed a comparative sentiment analysis of ride-hailing services with DL methods. The hybrid model outperformed other models consistently, with the highest accuracy on all four Indian apps: Ola with 98.98%, Uber with 98.06%, Rapido with 96.83%, and Namma Yatri with 94.91%.

Although ML and DL approaches have been successful in sentiment analysis for ride-sharing services, several research gaps remain. There is a need for larger and more diverse datasets that can provide more detailed insights into specific ride-sharing service attributes, such as pricing, driver behaviour, and ride comfort.

This study validates that the hybrid LSTM-CNN model highly enhances sentiment classification, performing better than other models with the highest accuracy on several ride-sharing platforms. Future work should include transformer-based models, larger datasets, and better sentiment classification methods to improve the accuracy and usability of sentiment analysis in ride-hailing services.

III. METHODOLOGY

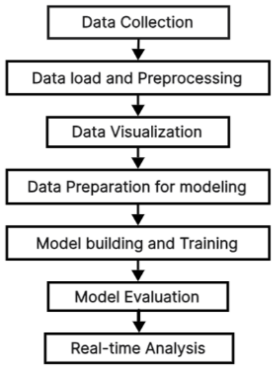

Fig 2: Data Processing Flowchart

The suggested methodology adopts a systematic workflow, as illustrated in Fig. 2. It is a sequence of steps where each provides systematic handling, transformation, and interpretation of the data to improve model performance and reliability.

It begins with the process of data collection, in which raw data is collected from different sources.

reviewId	userName	userImage	content	score	thumbsUpCount	reviewCreatedVersion	at	replyContent	repliedAt	appVersion
25305d90-1cfd-401a-b9bd-	Akhilesh Mishra	https://play-lh.googleusercontent.com/a-/ALV-	Excellent Service with reasonable priceðŸ'	5	8	7.2.5	16-03-2025 15:27	We're delighted with the 5-star rating and	16-03-2025 15:49	7.2.5
834ed38a-b5f2-4199-afba-	Pranit Mogal	https://play-lh.googleusercontent.com/a-/ALV-	best app for comfortable riding and	5	44	7.2.5	16-03-2025 15:20	Thanks for your feedback! ðŸ™Œ	16-03-2025 15:37	7.2.5
079eb426-300c-4404-8ce0-	Rahul sahu	https://play-lh.googleusercontent.com/a-/ALV-	charged wrong by the app	1	0	7.2.5	16-03-2025 15:17	We're alarmed looking at your review. We're here	16-03-2025 15:38	7.2.5
3f5d7f02-0b71-4104-a500-	dakshay B.A	https://play-lh.googleusercontent.com/a/ACg8ocLIW2Ss09	Not too bad, but could be better.	3	12	7.2.5	16-03-2025 15:08	Hi Dakshay, we're alarmed looking at your review. We're	16-03-2025 15:31	7.2.5
b5216a22-967a-4f5a-8b60-dd286ff8dc	Sambit Mahapatra	https://play-lh.googleusercontent.com/a/ACg8ocJWF18HprPWNdjgYBi8sWPinXvfd	[illegible]	2	30		16-03-2025 15:05	We are concerned about the 1-star rating and would like to know the	16-03-2025 15:32	
6a586f7c-2247-40bb-8099-6374d4630	Ravikumar Meesala	https://play-lh.googleusercontent.com/a-/ALV-UjXCexQ9M9uPiywPKB	good	5	0	7.2.5	16-03-2025 15:01	Thanks for your feedback! ðŸ™Œ	16-03-2025 15:24	7.2.5
88b9894b-cbf6-4776-a79a-c9b0fe21f3	Jatin Patel	https://play-lh.googleusercontent.com/a/ACg8ocKOD-tTeKQE9_hLXRgCEaWm	No bike service while must need ðŸ'Ž	1	35	6.1.6	16-03-2025 14:43			6.1.6
cc5cc2bd-36c0-4481-9def-	Rajesh Karamtothu	https://play-lh.googleusercontent.com/a-/ALV-	good ðŸ'ðŸ»ðŸ'Š	5	38	7.2.5	16-03-2025 14:41	We are delighted to hear such encouraging	16-03-2025 15:17	7.2.5

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Fig 3: Dataset

A. Data Collection:

As shown in Fig. 3, the dataset comprises user reviews of Ola extracted from the Google Play Store, including attributes such as review ID, user name, Review content, score, engagement metrics, and the date. This structured format enables a thorough analysis of user sentiment and engagement behaviour across different ride-hailing applications. The data comprises 160,000 user reviews gathered from the Google Play Store for four large ride-hailing applications: Ola, Uber, Rapido, and Namma Yatri, with 40,000 reviews for each application. Reviews were scraped only for the year 2025 using the Google-Play-Scraper Python library.

B. Data Preprocessing:

As the reviews were done in more than 1 language, a language translation process was required. The non-English reviews were translated into English with the Google Translate API. To minimize API expenses and processing time, batch translation was employed, where multiple reviews were translated at once. This allowed the entire dataset to be translated into English first before continuing further with processing.

Table 1. Text Preprocessing

Steps	Review (before)	Review(After)
Translation	मैं इस सेवा को फिर से उपयोग करूंगा!	I will use this service again!
lowercasing	Ride Was GREAT!	ride was great!
Stop word removal	It was a very good ride.	Good ride
lemmatization	The drivers were running late	The driver be run late
Emoji removal	Excellent Service with reasonable price 👍	Excellent Service with reasonable price
Special character removal	Service was bad!!	Service was bad

1. Text preprocessing:

Preprocessing is necessary for cleaning text data before sentiment analysis. Major preprocessing steps are identified in Table 1 with examples. Lowercasing normalizes the text by converting all characters into lowercase, making it more consistent and preventing case sensitivity problems. Redundancy is prevented, and model performance is improved by making words like "Good" and "good" the same. Stop word removal eliminates common words that do not contribute to sentiment, making models more efficient. Lemmatization lowers words to the root word, making text more consistent. Emoji removal eliminates non-text symbols that prevent sentiment from being identified. Finally, special character removal eliminates punctuation and symbols, resulting in a clean and neat dataset for accurate sentiment classification.

A three-class sentiment classification approach was used in rating transformation to categorical sentiment labels. A rating of 4 or 5 was labelled positive(2), a rating of 3 as neutral(1), and 1 or 2 rating reviews as negative(0). This classification enabled a more detailed sentiment analysis compared to a simple binary classification(positive/negative)

2. Feature engineering:

It was utilized to transform text into numerical representations. TF-IDF was utilized to prioritize words that appear often within a review but infrequently in the dataset as a whole. Word embeddings were created using a Keras tokenizer, and the sequences were padded to the same length before utilization within deep learning models.

C. Machine Learning Models:

Two ML algorithms, the DT classifier and the RF classifier, were utilized with Scikit-learn for sentiment classification.

- DT algorithm is a supervised ML method used for both classification and regression problems. It is called so because of its tree-like structure, where class labels are leaves and features or conditions are branches. This technique is highly known for being easy to comprehend, interpret, and visualize[15]. In the conducted research, the DT model was used for sentiment analysis on user reviews of several ride-hailing apps. The accuracy results revealed differing performance on the different platforms, at 79% for Uber, 71% for Ola, 70% for Namma Yatri, and 64% for Rapido. These differences reflect differences in the complexity and pattern of sentiment in user feedback across the apps.

- RF is a collection of decision trees in which each tree is constructed using a bootstrapped copy of the training set. Every tree is constructed through the process of recursive partitioning, where the root node, the same node-splitting process is repeated over and over until some stopping criteria are satisfied. Its strength for prediction lies in the summation of numerous weaker learners like DT. The performance is particularly excellent if the correlations between the trees in the woods are low[16]. In the performed research, the RF model was used for sentiment analysis of user ratings for different ride-hailing apps. The model performed well on different platforms, with 89% for Ola, 86% for Namma Yatri, 84% for Uber, and 80% for Rapido. These values demonstrate the strength of the RF model in recognizing subtle patterns within the dataset and enhancing the performance of classification compared to the DT model.

D. Deep Learning Models:

To enhance sentiment classification accuracy, three deep learning models were explored:

- Long Short-Term Memory(LSTM) is a complex RNN to combat the vanishing gradient issue through memory cells storing long-term dependencies.

LSTM has an input layer, hidden layer, stable cell state for information flow, and output layer[17]. In LSTM-based sentiment analysis of ride-hailing app reviews, Ola reached 70% accuracy, Uber (63%), Rapido(58%), and Namma Yatri(57%). Misclassifications were witnessed on the account of successfully identified sentiment trends.

- GRU is a reduced form of LSTM, which is created to enhance efficiency. GRU employs an update gate to regulate information to be retained and a reset gate to monitor the effect of previous states, replacing individual input and forget gates[18]. In the sentiment analysis of the ride-hailing reviews using GRU, Ola scored the highest accuracy of 71% and Namma Yatri scored the lowest accuracy of 57%. There were misclassifications based on data imbalance, affecting the model's effectiveness in generalizing across sentiment categories.
- The hybrid LSTM-CNN model consists of the integration of CNN and LSTM networks. Spatial feature extraction capabilities of CNNs are complemented with the temporal sequence modelling ability of LSTMs for better performance[19]. With this model, there was very high accuracy for sentiment analysis, including Ola at 98.98%, Uber at 98.06%, Rapido at 96.83%, and Namma Yatri at 94.91%. incorporating LSTM and CNN improved feature extraction, thereby enhancing performance.

All models are trained on a train-test split mode(80% train, 20% test). Deep learning models are trained for 5 to 10 epochs with a batch size of 64.

E. Model Evaluation:

All models are systematically analysed with several performance metrics. Training accuracy, test accuracy, and validation accuracy are assessed to check how well the model is learning and generalizing, A confusion matrix is calculated to check correct and incorrect predictions to identify patterns in misclassifications. Additionally, a classification report is generated that gives precision, recall, and F1-score for an even better understanding of predictive performance. For testing the model's class differentiation ability, the ROC curve is charted, and the AUC score is calculated, providing both a visual and a numeric indicator of classification effectiveness.

F. Real-time analysis:

A real-time sentiment analysis was carried out using the Hybrid LSTM-CNN model, enabling a thorough assessment of user comments in a variety of ride-hailing apps. Further, a comparative analysis of various ride-hailing platforms was done, offering insightful information regarding user sentiment patterns.

IV. RESULTS AND ANALYSIS

Table 2. Test Accuracy of Models

APP	DT	RF	LSTM	GRU	Hybrid LSTM-CNN
Ola	71%	89%	70%	71%	**98.98%**
Rapido	64%	80%	58%	57%	**96.83%**
Namma Yatri	70%	86%	57%	56%	**94.91%**
Uber	79%	84%	63%	64%	**98.06%**

Table 2 display the accuracy of different models in sentiment analysis of user reviews from four ride-hailing apps the hybrid LSTM-CNN is the best among all the models and is consistently superior to others with the highest accuracy in all apps, 98.98% for Ola, 98.06% for Uber, 96.83% for Rapido, and 94.91% for Namma Yatri. These results highlight that while RF is the most accurate among ML models, the Hybrid LSTM-CNN model significantly improves, which proves that convolutional and recurrent layers together improve sentiment classification performance.

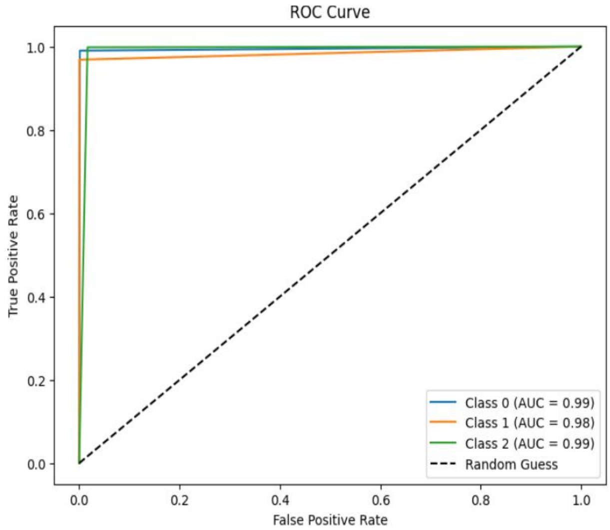

Fig 4: ROC Curve for Ola Application

The Receiver Operating Characteristic (ROC) curve is a graphical analysis tool to examine the performance of a classification model, especially applied in ML and DL models. The Area Under the Curve (AUC) is then utilized to tabulate the summary of the ROC curve in the form of one value [20]. The Fig.4 shows the ROC curve of Ola's sentiment classification by the Hybrid LSTM-CNN model. The AUC scores are high(0.99 for negative and positive classes, 0.98 for neutral), which indicates great classification performance.

Mathematical definition of AUC is:

$$AUC = \int_0^1 TPR(FPR)d(FPR)$$

Where:

TPR(True Positive Rate) = $\frac{TP}{(TP+FN)}$

FPR(False Positive Rate) = $\frac{FP}{(FP+TN)}$

The curves lying close to the top-left corner suggest very few false positives, indicating the model's ability to predict user sentiments accurately.

```
 Real-Time Review Analysis
Original Text: not bad
Given Rating: 3
Predicted Sentiment (Model): Neutral
Final Sentiment: Neutral
```

Fig 5: Real-Time Sentiment Prediction

Fig. 5 shows the Hybrid LSTM-CNN model's real-time sentiment analysis output. The input review, "not bad", is labelled with a given rating of 3, expressing a neutral sentiment. The model properly predicts the sentiment as neutral, consistent with the rating. This shows the effectiveness of the model in processing real-time user reviews by correctly understanding sentiment. The Hybrid LSTM-CNN model increases classification performance and is a reliable approach to sentiment analysis for ride-hailing applications. The same sentiment analysis technique with the Hybrid LSTM-CNN model has been used for all ride-hailing apps, such as Ola, Uber, Rapido, and Namma Yatri.

Fig 6: Ola Negative Reviews World Cloud

The word cloud representation of Ola's negative reviews with the most frequently occurring issues mentioned is shown in the Fig. 6. Customer care, worst app, bad experience, and extra money are major concerns, reflecting dissatisfaction with customer support, app functionality, and surprise charges. Phrases such as cancel ride and auto driver reflect frequent cancellation of rides and issues with drivers.

The same was done for Uber, Rapido, and Namma Yatri, but Ola's word cloud is shown here for brevity. These findings enable us to determine the most important service issues and areas of improvement.

The comparative sentiment distribution results among these apps are shown in Fig. 7. The sentiment distribution is divided into 3 classes: positive, neutral, and negative.

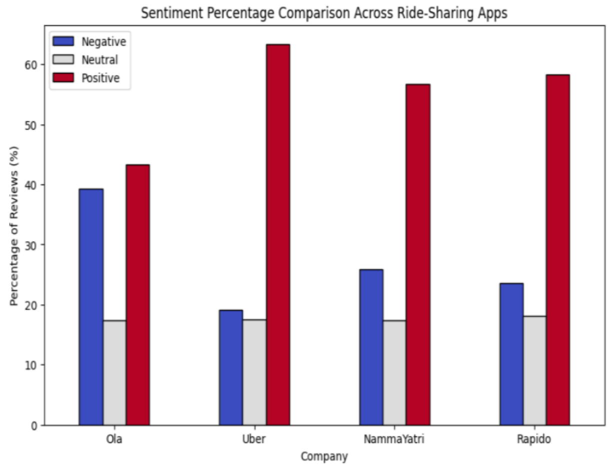

Fig 7: Sentiment Comparison Across Apps

As indicated in Fig. 7, Uber shows the highest percentage of positive reviews, reflecting greater levels of customer satisfaction than Ola, Rapido, and Namma Yatri. On the other hand, Ola shows a comparatively higher percentage of negative reviews, implying possible issues with the services that need to be addressed. Moreover, the neutral sentiment ratio is fairly stable across all platforms, with minor differences.

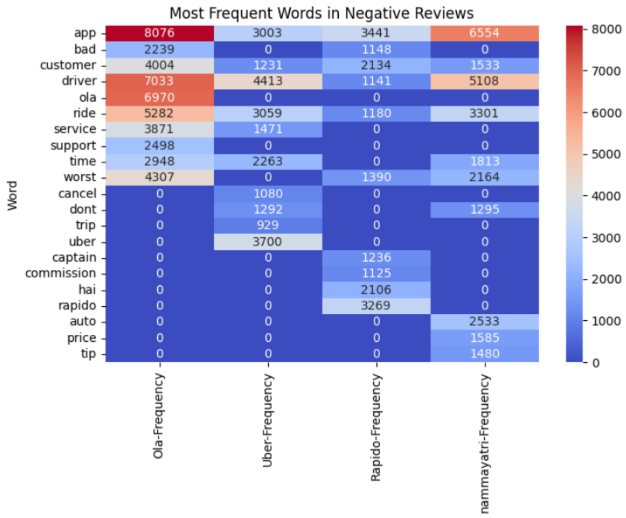

Fig 8: Frequent Negative Words Used

A heatmap visualization of the most common words in negative reviews of Ola, Uber, Rapido, and Namma Yatri is displayed in the Fig.8. The intensity of colour indicates how frequent each word is, with red and orange colours showing more frequent occurrences. The heatmap identifies the most frequent negative words on all platforms to be "app", "driver", "ride", "customer", and "worst". Ola shows the highest occurrence of negative words like "app"(8076), "driver"(7033), and "ride"(5282), reflecting technical app-related glitches, driver misconduct, and ride cancellation. In a similar way, Uber and Rapido report concerns relating to "cancel", "trip", and "commission", whereas Namma Yatri users complain most about "price" and "auto", reflecting fare dissatisfaction.

Actionable insights:

- Improving driver training: Most of the complaints are about driver behaviour and cancellations, which can be addressed with improved driver training and stricter policies
- Technical improvements: Repeated instances of "app" indicate a need for performance optimization, bug fixes, and intuitive UI improvements.
- Fare transparency: Ride-hailing services must implement transparent fare breakdowns to reduce user discontent over fares and commissions.
- Customer support enhancement: firms must enhance their support structures to efficiently resolve complaints, especially to process refunds, cancellations, and resolve disputes.

By resolving these key points, ride-hailing platforms can enhance service quality, customer retention, and increase user satisfaction.

V. DISCUSSION

This research brings out the effectiveness of deep learning models, more specifically the hybrid LSTM-CNN, in classifying the user sentiment of ride-hailing apps. The model surpassed traditional ML methods in the sense that it could recognise certain sentiment patterns within textual data.

Sentiment analysis found that Uber receives the most positive comments, followed by a greater percentage of negative comments for Ola, based on price and ride cancellations. Complaints across platforms about driver behaviour, surprise charges, and support from customers are common.

The research does have some limitations. The data used is a Google Play Store review dataset, which may not represent all users. Translation of reviews that are not in English may also bring minor inaccuracies.

Future research can investigate multimodal sentiment analysis based on voice feedback on social media data for a richer understanding of user experiences.

VI. CONCLUSION

This study offers a comparative sentiment analysis of user feedback in various ride-hailing apps (Ola, Uber, Rapido, and Namma Yatri) with machine learning and deep learning models, including a hybrid LSTM-CNN model. The results reflect considerable variation in user satisfaction, service quality, and pain areas among these apps. The suggested hybrid model offers greater classification accuracy and stability in sentiment analysis than conventional methods.

The study adds value to natural language processing(NLP) and consumer analytics by offering data-driven insights into users' experiences on rival ride-hailing companies. The comparative methodology enables service companies to pinpoint strengths, rectify customer issues, and improve their platforms according to actual feedback.

Further studies can investigate multimodal sentiment analysis by including more user data such as ride duration, pricing of fares, and interactions with drivers. Moreover, aspect-based sentiment analysis(ABSA) may yield more in-depth insights into individual service aspects such as pricing, safety, app user experience, and driver behaviour. Furthermore, newer transformer-based models (BERT, GPT) and explainable AI (XAI) methods can improve classification accuracy and explainability, thus enabling sentiment insights to be more useful to businesses and policymakers alike. In addition, adding geospatial analytics could help analyse regional variations in user sentiment, enabling ride-hailing companies to implement location-specific service improvements

VII. REFERENCES

[1] N. K. R. Pothireddy, "THE ROLE OF BIG DATA IN RIDESHARING ECONOMICS," *INTERNATIONAL JOURNAL OF COMPUTER ENGINEERING AND TECHNOLOGY*, vol. 14, no. 3, pp. 260–282, Dec. 2023, doi: 10.34218/IJCET_14_03_026.

[2] M. S. Mahmud, A. Jaman Bonny, U. Saha, M. Jahan, Z. F. Tuna, and A. Al Marouf, "Sentiment Analysis from User-Generated Reviews of Ride-Sharing Mobile Applications," in *Proceedings - 6th International Conference on Computing Methodologies and Communication, ICCMC 2022*, Institute of Electrical and Electronics Engineers Inc., 2022, pp. 738–744. doi: 10.1109/ICCMC53470.2022.9753947.

[3] K. L. Tan, C. P. Lee, K. M. Lim, and K. S. M. Anbananthen, "Sentiment Analysis With Ensemble Hybrid Deep Learning Model," *IEEE Access*, vol. 10, pp. 103694–103704, 2022, doi: 10.1109/ACCESS.2022.3210182.

[4] P. Nandwani and R. Verma, "A review on sentiment analysis and emotion detection from text," Dec. 01, 2021, *Springer*. doi: 10.1007/s13278-021-00776-6.

[5] M. Rana and M. Bhushan, "Machine learning and deep learning approach for medical image analysis: diagnosis to detection," *Multimed Tools Appl*, vol. 82, no. 17, pp. 26731–26769, Jul. 2023, doi: 10.1007/s11042-022-14305-w.

[6] A. Halbouni, T. S. Gunawan, M. H. Habaebi, M. Halbouni, M. Kartiwi, and R. Ahmad, "Machine Learning and Deep Learning Approaches for CyberSecurity: A Review," 2022, *Institute of Electrical and Electronics Engineers Inc.* doi: 10.1109/ACCESS.2022.3151248.

[7] J. Anthal, A. Upadhyay, Y. Indulkar, and A. Patil, "Twitter Sentimental Analysis & Algorithm Comparison for Uber & Ola Using 'R,'" *International Journal of Future Generation Communication and Networking*, vol. 13, no. 1s, pp. 352–358, 2020.

[8] Bhagaskara. Wiguna, H. Herlawati, and A. Yusuf, "Sentiment analysis of on-demaind ride-hailing systems, using svm and nb," *Penelitian Ilmu Komputer Sistem Embedded and Logic*, vol. 11, pp. 401–414, 2023.

[9] V. Atina and P. Srisuk, "Sentiment Analysis of Grab App Reviews with Machine Learning Approach."

[10] R. Sathya, S. Sahu, and K. Ritesh, "Uber Data Analysis using Neural Networks," 2021. [Online]. Available: www.tnsroindia.org.in

[11] Md. Saymon Ahammad, S. A. Sinthia, Md. Muaj Chowdhury, N.-A.-A. Asif, and Md. Nurul AfsarIkram, "Sentiment Analysis of Various Ride Sharing Applications Reviews: A Comparative Analysis Between Deep Learning and Machine Learning Algorithms," 2024, pp. 434–448. doi: 10.1007/978-3-031-69986-3_33.

[12] U. B. Mahadevaswamy and P. Swathi, "Sentiment Analysis using Bidirectional LSTM Network," in *Procedia Computer Science*, Elsevier B.V., 2022, pp. 45–56. doi: 10.1016/j.procs.2022.12.400.

[13] F. Rustam, M. Khalid, W. Aslam, V. Rupapara, A. Mehmood, and G. S. Choi, "A performance comparison of supervised machine learning models for Covid-19 tweets sentiment analysis," *PLoS One*, vol. 16, no. 2, Feb. 2021, doi: 10.1371/journal.pone.0245909.

[14] M. Becerra-Salas and H. N. Roa, "Evaluating Uber Customers' Perception Through Machine Learning Techniques: A Case Study in Ecuador," in *Proceedings - 2023 International Conference on Computational Science and Computational Intelligence, CSCI 2023*, Institute of Electrical and Electronics Engineers Inc., 2023, pp. 771–776. doi: 10.1109/CSCI62032.2023.00131.

[15] H. Dabiri, V. Farhangi, M. J. Moradi, M. Zadehmohamad, and M. Karakouzian, "Applications of Decision Tree and Random Forest as Tree-Based Machine Learning Techniques for Analyzing the Ultimate Strain of Spliced and Non-Spliced Reinforcement Bars," *Applied Sciences (Switzerland)*, vol. 12, no. 10, May 2022, doi: 10.3390/app12104851.

[16] J. Hu and S. Szymczak, "A review on longitudinal data analysis with random forest," Mar. 01, 2023, *Oxford University Press*. doi: 10.1093/bib/bbad002.

[17] H. N. Bhandari, B. Rimal, N. R. Pokhrel, R. Rimal, K. R. Dahal, and R. K. C. Khatri, "Predicting stock market index using LSTM," *Machine Learning with Applications*, vol. 9, p. 100320, Sep. 2022, doi: 10.1016/j.mlwa.2022.100320.

[18] S. Mahjoub, L. Chrifi-Alaoui, B. Marhic, and L. Delahoche, "Predicting Energy Consumption Using LSTM, Multi-Layer GRU and Drop-GRU Neural Networks," *Sensors*, vol. 22, no. 11, Jun. 2022, doi: 10.3390/s22114062.

[19] A. Nazir *et al.*, "A deep learning-based novel hybrid CNN-LSTM architecture for efficient detection of threats in the IoT ecosystem," *Ain Shams Engineering Journal*, vol. 15, no. 7, Jul. 2024, doi: 10.1016/j.asej.2024.102777.

[20] F. S. Nahm, "Receiver operating characteristic curve: overview and practical use for clinicians," *Korean J Anesthesiol*, vol. 75, no. 1, pp. 25–36, Feb. 2022, doi: 10.4097/kja.21209.