Sentiment Analysis from User-Generated Reviews of Ride-Sharing Mobile Applications

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***Abstract*— Smartphone applications play an increasingly significant part in our everyday lives, and their use has skyrocketed. The Google Play Store is a well-known plat-form through which one may obtain various Android applications whereas ap-plication like Ridesharing play a significant role in delivering public services more efficiently and effectively, as seen by the widespread adoption of many different types of innovative applications. This study focuses on users' reactions to these ridesharing applications, and it employs sentiment analysis to extract emotions from text reviews posted on the Google App Store platform given by the users. The primary goal is to examine the perspectives of customers and users of these applications. A total of 1818 data was gathered from the Google Play Store and divided into three categories: positive, negative, and neutral. The model was evaluated using the CNN, LSTM, and DistilBERT algorithms, with DistilBERT outperforming the others and achieving the highest accuracy of 98.84 %.**

Keywords— Rideshare Apps, CNN, LSTM, DistilBERT, NLP, Sentiment Analysis.

I. Introduction

Drivers of privately owned automobiles who want to give rides and passengers who want to get rides often utilize a network to coordinate the sharing of individual automobile trips for which the passengers pay, this is basically the concept of ride sharing [1]. In recent years, ride-sharing services have grown in popularity in urban areas. Traditional taxicab services have been challenged by the advent of dynamic ride-sharing services in particular [2]. People are increasingly relying on ridesharing services in their daily lives, which was really not the case in previous decades. Many transportation establishments, including Uber, Pathao, Sohoz, OBHAI, Digital Ride, GO CNG, Uber Lite, Piickme, and Lyft, have adopted a digital platform-based business model in which they connect riders and customers principally through smartphone applications. According to a recent study, the number of individuals using ride-sharing apps worldwide is expected to approach half a billion by 2021. Ride-sharing apps are expected to be used by 540 million individuals worldwide [3].

As a result of urbanization and development, mobile applications are becoming more available to people, and ridesharing applications, in particular, are contributing to people's comfort and time savings. The classification of emotions (positive, negative, and neutral) inside data using text analysis techniques is known as sentiment analysis. Deep learning is a type of ML that solves complex issues by combining numerous algorithms in a sequence of events. Through its complex algorithm chain, the neural network may learn to correct itself in deep learning. Deep learning models can split down phrases, paragraphs, and entire documents into separate units, providing more accurate results than conventional natural language processing algorithms [4].

Because there are so many Ride Sharing-related apps on the Google Play Store, this research attempts to employ deep learning techniques to extract the emotion of users of those apps. We used techniques like CNN, LSTM, and DistilBERT in this study. The reviews are valuable to both the providers of ride-sharing apps and the users of those apps. This will provide a unique viewpoint on app users, as they will be able to easily submit their valuable feedback to the Google Play store's review section.

II. Related Works

Although there are many studies in the area of ride-sharing systems, deep learning methods are seldom used. As a result, topics such as sentiment analysis utilizing deep learning techniques and ride sharing have been studied.
Andrea Chiorrini et. al. [5] evaluate the effectiveness of BERT models for sentiment analysis and emotion detection using real-world twitter datasets. The BERT Base was utilized as a reference model in this study, both in its uncased and cased versions. This model was enhanced with the addition of a fully connected layer along with a SoftMax layer for classification, in which the amount of neurons is equal to the number of classes, with 3 for sentiment analysis and 4 for emotion detection. The models attain a greater accuracy of 92% for sentiment when utilizing the cased version of BERT analysis, but 90% for emotion recognition when using both the cased and uncased versions of BERT.
Henry Gao et.al. [6] utilized the restaurant review dataset as a comparative study of NLP to illustrate the difference between positive and negative sentiment. 1000 data were acquired from Kaggle, and because they employed an unsupervised approach, the data labels were deleted. Pretrained models DistilBert (a distilled version of BERT), VEDER (lexicon-based tool), and fine-tuned VADER were used in conjunction with LSTM to evaluate the output of the model's polarity for restaurant reviews and calculate the TP,

TN, FP, FN, and accuracy, with DistilBert having the highest accuracy of 92.4%.

Acheampong Francisca Adoma et.al. [7] compares the output of each candidate model to the output of the remaining candidate model to see how efficient BERT, Roberta, DistilBERT, and a pretrained transformer XLNET models are in analyzing emotions from texts. The implemented models are fine-tuned to differentiate seven emotions from the ISEAR's emotion classes, including anger, contempt, sorrow, fear, humiliation, and guilt. The data was decreased from 7666 to 7589 after preprocessing. Roberta achieved a greater accuracy of 0.7431 after adopting the pre-trained transformer models.

Md. Sabab Zulfiker et. al. [8] examine user perceptions of two prominent transportation services provided via online, 'Uber' and 'Pathao,' from the perspective of Bangladesh. Only English texts were used by the authors to perform sentiment analysis. With an accuracy of 87%, the Naive Bayes classifier surpassed SVM and Decision Tree.

Chi Sun et. al. [9] created an auxiliary sentence in order to convert (T)ABSA from a single sentence classification task to a sentence pair classification task in this study. The authors acquired fresh state-of-the-art results after fine-tuning the pre-trained BERT algorithm on the sentence's pair classification test. For fine-tuning, they employed the pre-trained uncased BERT-base model. BERT-pair beats other models on aspect detection and sentiment analysis by a significant margin on the SentiHood dataset in experiment 1 - TABSA, with a 9.4 macro-average F1 and 2.6 accuracies improvement over DmuEntnet. In experiment 2 - ABSA, they discovered that BERT-single performed better on these two subtasks, while BERT-pair performed even better than BERT-single.

Venkata Himakar Yanamandra et. al. [10] explore how people identify tobacco products and how they perceive them in texts taken from two popular social media platforms: Twitter and Reddit. For Twitter, this work uses semi-supervised learning on Reddit text with manually annotated text. They employed commonly used text classification models including FastText, BERT, Roberta, and DistilBERT to execute benchmarking studies for sentiment and product identification in Reddit and Twitter. Sentiment Identification in Twitter, Product Identification in Reddit, and Sentiment Identification on Reddit are the three experiments. For all measures in this paper's experiments, Roberta surpasses all other models. DistilBERT performs the competition by requiring substantially less time and computing power for pre-training and fine-tuning.

Shiyang Liao et. al. [11] offered a method for understanding scenarios in the real world with the sentiment analysis of Twitter data and deep learning techniques . They separated the MR (collection of movie reviews for training) and STS Gold Dataset (collection of real tweets for testing) datasets into positive and negative categories. They created a basic convolutional neural network model and tested it on a benchmark dataset, obtaining an average accuracy of 75.39%, which is close to the training dataset's result.

Jinghua Zhao et. al. [12] developed a technique for mining information created by users on social networking sites and predicting user personalities using Bayesian Network, RF, SVM, and Attention-based LSTM algorithms. The study uses several forms with the LSTM model to predict the personality traits of social network users by converting users' theme preferences and text sentiment data into attention information. The Attention-based LSTM algorithms acquired the greatest Precision, Recall, and F1-measure score after establishing the data sets that are randomly categorized according to 7:3 and the training set is trained for ten times and the test set is tested for ten times.

Praphula Kumar Jain et.al. [13] propose a method of sentiment analysis where the Keras word embedding strategy was applied on Airline quality and Twitter airline sentiment datasets using a CNN-LSTM model with dropout, max pooling, and batch normalization. When the proposed CNN-LSTM was compared to the results of the LR,DT, SVM, NB,CNN,LSTM, the proposed technique had the highest accuracy of 90.2 %.

Ananna Saha et al. [14] In this paper, they are discussing depression contents in various social media platforms. They used different traditional classifiers and Random forest classifiers gave the highest accuracy from others. Tapasy Rabeya et al. [15] This paper presented a Bengali song review of a specific YouTube channel. They used a backtracking algorithm for expressing opinions on this song review. This algorithm gained 71.23% accuracy.

Dr. Akey Sungheetha et al. [16] In this proposed work, we introduce TransCap, an innovative Capsule concept for classifying feature viewpoints. The above task highlights the problem of records which are labeled at the aspect-level also with assistance of abundant manuscript information. Archit Sharma et al. [17] This paper demonstrated the importance of sentiment analysis in stock market forecasting. They employed two distinct algorithms, LSTM and ARIMAX with and without SA. When sentimental analysis is used, the outcome of these two algorithms is improvement.

Lakshmi Prayaga et al. [18] This article reports the findings and conclusions from a comparison of sentiment classification applicable to YouTube and Twitter information on a range of things. The point of the study would have been to look for variations in opinions expressed on various social media sites. In other words, did the social media platform have any effect here on a person's affirmation of feelings?

Dr. J. Samuel Manoharan et al. [19] ELM refers to Extreme Learning Machines. To achieve a quicker learning capacity and much less calculation time with minimal intervention, the ELM essence must be integrated. This survey article contains the true essence of ELM as well as a brief explanation of a classification method. This scientific report contains comprehensive information on ELM different versions for multiple classification activities.

III. Proposed Methodology

The data for ridesharing text review were gathered manually from Google Play Store and as they were unlabeled, we divided them into three categories: positive, negative, and neutral. As the data were unstructured, so after preprocessing ,we applied three different techniques which are CNN, LSTM, DistilBERT to test our model.

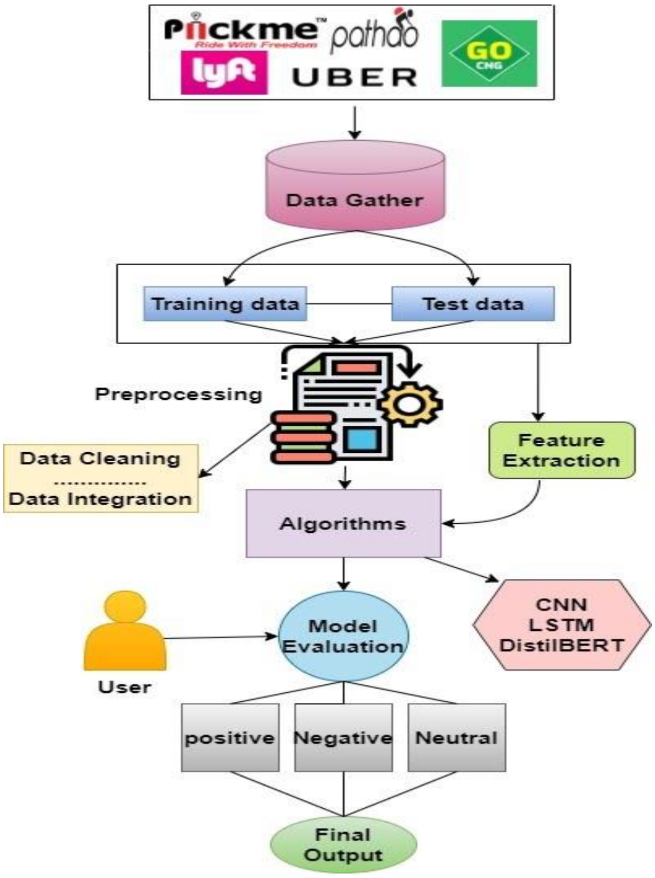


Fig. 1. Our overall Work Procedure of model for ridesharing apps review.

A. Data Collection

Data is the most important part of creating a research study. In this study, we compiled reviews of ride-sharing apps from the Google Play Store, including Uber, Lyft, GO CNG, and Pathao. Nearly 1818 data sets were obtained from these applications, and they were divided into three categories (positive, negative, and neutral). There are 718 positive data points, 624 negative data points, and 476 neutral data points. There are numerous datasets available online, but the dataset that has been utilized is a one-of-a-kind and up-to-date dataset that we have prepared ourselves.

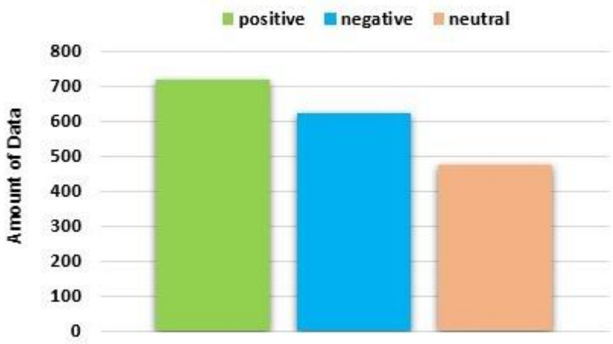


Fig. 2. Bar chart of our Ridesharing apps review data.

B. Preprocessing Process

NLP relies heavily on data preprocessing. Data preprocessing is the way of converting unstructured data to well-formed data. When we gather information from various sources then some of the information is Grammarly wrong or information is not attainable. We use some preprocessing methods that can help us to get well-structured data. Data cleaning means the processing of missing data to fulfill, some rows are deleted because they are missing [20]. In the dataset we can see the same data written in different ways, we solved this problem so that they cannot conflict with each other. Data transformation is used for the implementation of the data. Data reduction focuses on the reduction of specific sorts of data, most notably the quantity of data. Tokenization means splitting the data into parts and this part is called token. A machine can define this token easily. That's why we have used tokenization which is one of the most important preprocessing processes. In our proposed work, two models are using preprocessing methods and another one DistilBERT is a pretrained model.

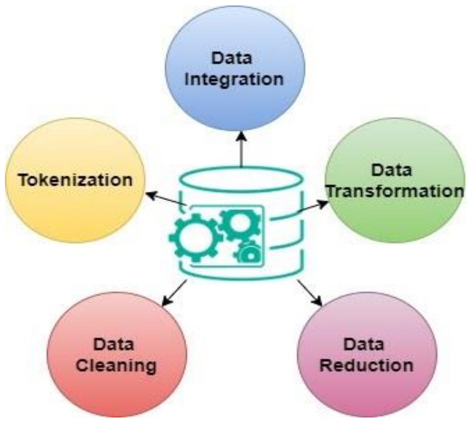


Fig. 3. Data Preprocessing steps of CNN & LSTM.

TABLE I. DATASET SAMPLE WITH CATEGORY AND LABEL

Sentences	Category	Label
Good service for us, we can get vehicles easily.	positive	0
App is good but didn't work properly on the Huawei 2017 model.	negative	1
Extremely frustrating app. you need to uninstall and install every time you want to use it	neutral	2

C. Convoloution Neural Network Model

CNN is one of the most favorable approaches to developing ML algorithms [21]. CNN is made up with three layers: one is convolution layer, Pooling layer, and Fully connected layer.

(i) In the Conv1D layer, filters were 32, kennel size 3 and activation function was “relu”.
(ii) Adding a Global MaxPooling layer.
(iii) Dropout value was 0.5.
(iv) Using the dense layer with an activation function which is “SoftMax”.
(v) In the model compiling section, we used an optimizer called ‘Adam’ and used a loss function called ‘categorical_crossentropy’.

Finally, the model is trained with batch size 256 and epochs 50.

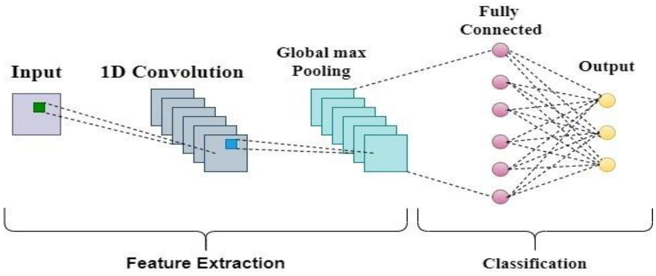


Fig. 4. Architecture of CNN Model [22].

D. *Long Short Term Memory Model*

LSTM is a type of Artificial RNN that can understand long term dependency relationships in deep learning. LSTMs are expressly intended to prevent the difficulties of long-term reliance [23]. LSTMs have such a filament configuration as well, but the repeating module, on the other hand, has a unique architecture. In our model, we used an embedded layer then added a spatialDropout1D which value was 0.2. Applying LSTM size with Dropout layer and it was 0.5. We used an optimization function called “Adam”.

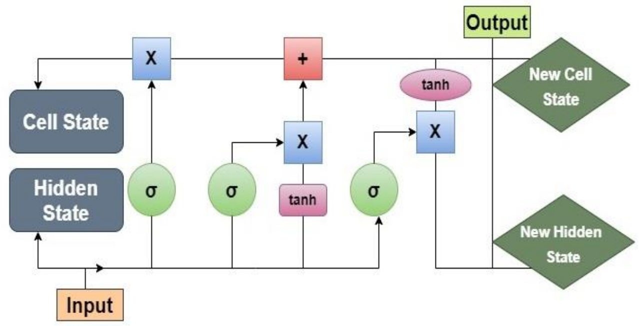


Fig. 5. Architecture of a typical LSTM Model [24].

E. *DistilBERT Model*

The DistilBERT is a BERT based architectural style that is restricted, quick, expensive, and reflective. As DistilBERT, we utilized the hugging face pre-trained trans-former model ‘DistilBERT-based multilingual-cased’ with ktrain. The model has al-ready been trained in several languages, including English. This model contains six folds, 788 dimensions, 12 heads, and 134 million parameters. This model had a maximum length of 1000 and a learning rate of 0.00002. The trained model consist of a batch size of 8 along with 7 epochs.

F. *Parameters Configuration*

Various parameters were used in our models such as batch size, epochs, maxln etc. This table displays the parameters we utilized and the length of parameters.

TABLE II. PARAMETERS CONFIGURATION OF OUR MODELS

Models	Batch-Size	Epochs	MaxLn
Glove+CNN	256	50	500
Glove+LSTM	256	50	500
DistilBERT	8	7	1000

IV. RESULTS ANALYSIS AND DISCUSSION

This figure represents the outperforms of the models [25]. We used three different DL models such as CNN, LSTM, and DistilBERT. Also we knew that CNN and LSTM models used preprocessed methods and DIstilBERT was a pretrained model. The accuracy of CNN model was 90.43% and LSTM gained 89.77%. On the other hand, DistilBERT, the pretrained model outperformed other two models and acquired a higher accuracy of 98.84%.

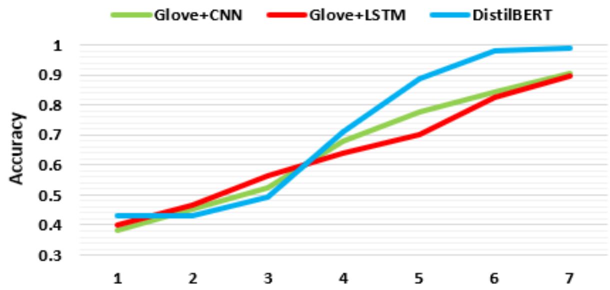


Fig. 6. Comparative analysis of the models for accuracy.

The figure presents the loss, validation-loss, accuracy and validation-accuracy of our three applied algorithms.

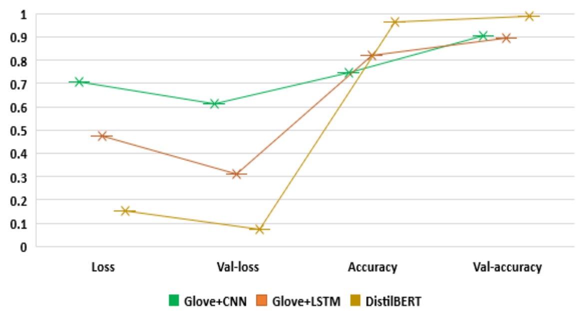


Fig. 7. Comparison between the loss, validation-loss, accuracy and validation-accuracy for the models.

Word Cloud means a set of phrases illustrated in various sizes. The larger and flashier the word exists, the further frequently it has seemed in a text document and the more significant it is [26]. The word cloud for our review dataset is presented below-

Fig. 8. Word cloud of the review dataset.

Subjective sentences normally relate to individual viewpoint, feelings, as well as decision, while unbiased statements relate to facts [27]. Subjectivity is indeed a float with a value between 0 and 1. Polarity as well as a floating value between -1 and 1.

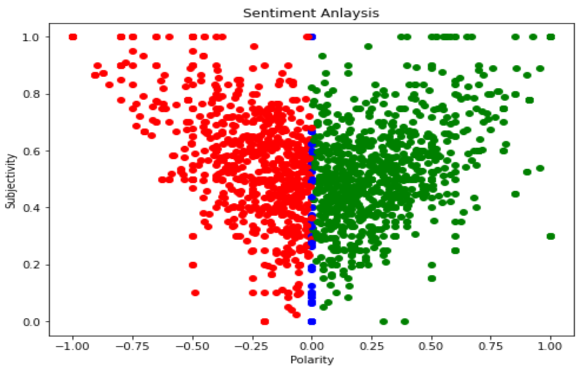


Fig. 9. Subjectivity and Polarity of the review dataset.

Along with accuracy the value of prison ,recall and F1-score is very necessary to evaluate a model [28]. From the table it is evident that for the all three classifiers (positive, negative and neutral) DistilBERT has achieved the highest value for Precision, recall and F1-score which results in proving that the DistilBERT performed better than Glove+CNN and Glove+LSTM.

TABLE III. EVALUATION MATRIX OF OUR MODELS

Models	Category	Precision	Recall	F1_Score
Glove+CNN	positive	0.90	0.92	0.91
	negative	0.97	0.81	0.88
	neutral	0.87	0.96	0.91
Glove+LSTM	positive	0.91	0.90	0.921
	negative	0.88	0.83	0.85
	neutral	0.90	0.94	0.92
DistilBERT	positive	0.99	0.99	0.99
	negative	0.98	0.99	0.98
	neutral	0.99	0.99	0.99

Sensitivity and specificity are statistical measurements of text classification's efficiency, with Sensitivity measuring the proportion of actual positives correctly and Specificity measuring the fraction of correctly detected negatives. From this graph, we can see that our model fared better in terms of sensitivity and specificity, but the pre-trained model DistiBert outperformed in terms of sensitivity, where both Glove+CNN and DistilBERT performed well in terms of specificity.

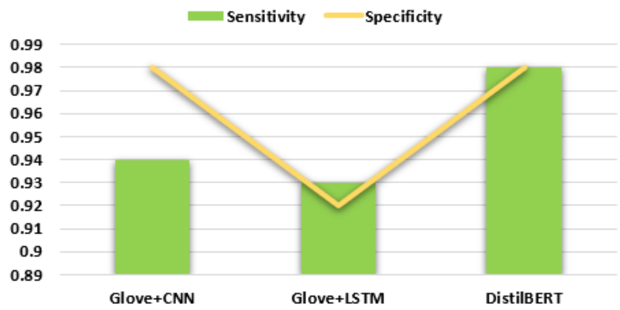


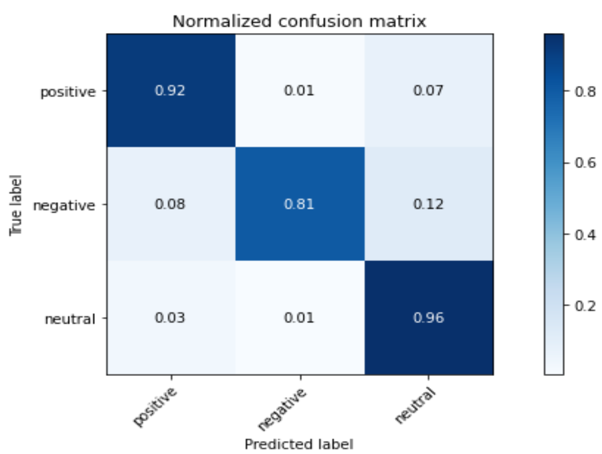
Fig. 10. Sensitivity and Specificity for three models.

The FPR is calculated by dividing the number of incorrect positive assumptions by the total number of negatives, and the FRP for Glove+LSTM is slightly higher. FNR, when expressed as a false negative, is an actual result in which the negative class is fully realized inconsistently, and DistilBert has the lowest FNR value. The proportion of cases who were absolutely recognized as negative compared to the total number of people who had negative test results is known as NPV, and in our model, all three algorithms had greater NPV values, with DistilBERT slightly higher than the other two. The total number of discoveries is divided by the number of false discoveries, which is known as FDR, and Glove+LSTM had a higher FDR score. The actual difference between expected and observed failures is averaged to get the MAE. The MSE is the difference in squares between the true and anticipated results. The standard deviation of predicted performance is referred to as the RMSE. Glove+CNN has slightly higher MAE, MSE, and RMSE than the other two models.

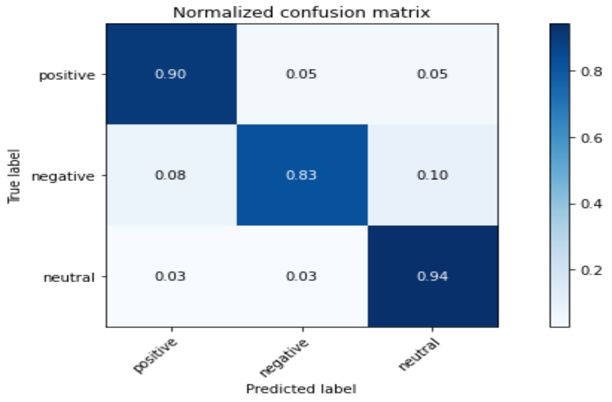
TABLE IV. ANALYTICAL COMPARISON BETWEEN THREE MODELS

Models	FPR	FNR	NPV	FDR	MAE	MSE	RMSE
Glove+ CNN	0.01	0.05	0.91	0.01	0.29	0.10	0.33
Glove+ LSTM	0.07	0.06	0.91	0.05	0.14	0.05	0.23
Distil-BERT	0.01	0.01	0.98	0.01	0.16	0.05	0.32

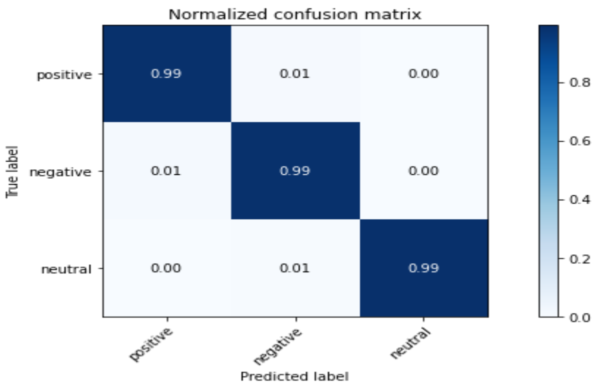
A confusion matrix is a visual representation of the prediction model's performance [29]. It is commonly known that most confusion matrices are described for binary classifications, but because we have a dataset with three class labels which are positive, negative, and neutral, as a result our confusion matrix is clearly a multi-class classification or 3x3 dimensional matrix. The figure of confusion matrices derived from our three algorithms are shown below.



(a) CNN



(b) LSTM



(c) DistilBERT

Fig. 11. Comparing Results of (a) CNN (b) LSTM and (c) DistilBERT.

It is clear from the graph that DistilBERT outperformed Glove+CNN and Glove+LSTM in terms of precision, recall, and F1-score.

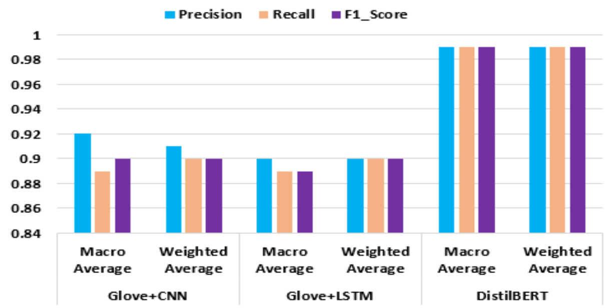


Fig. 12. Analogy between macro and weighted average of models.

This table demonstrates how well our model worked, as it is evident that we obtained the output we predicted for the input.

TABLE V. OUTCOME OF THE TRAINED MODEL FOR THE GIVEN INPUTS

Models	Sentences	Actual Category	Predicted Category
Glove+CNN	Best ride sharing service app ever	positive	positive
Glove+LSTM	Best ride sharing service app ever	positive	positive
DistilBERT	Best ride sharing service app ever	positive	positive

V. CONCLUSION AND FUTURE WORKS

In this study, we have extracted the sentiment of the users of ridesharing mobile ap-plications such as Uber, Lyft, GO CNG, and Pathao. The data was collected from google play store's review section where users give their opinion and experience through text mining. The opinion from the given reviews of the users or customers for a certain product or service is very popular nowadays. For our research, we processed the unstructured data into well-formed data.

After classifying the data into three different categories (positive, negative, neutral) and applying three popular deep learning methods: Glove+CNN, Glove+LSTM, and DistilBERT to the review dataset, our model performed exceptionally well, with the pretrained model DistilBERT achieving the highest accuracy. We want to work on a huge amount of dataset with a variety of algorithms in the near future to provide a comparison study.

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