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RESEARCH ARTICLE

Graph Neural Network for Smartphone Recommendation System: A Sentiment Analysis Approach for Smartphone Rating

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ABSTRACT The increasing demand for mobile phones has resulted in abundant online reviews, making it challenging for consumers to make informed purchasing decisions. In this study, we propose Graph Neural Network (GNN) models to classify mobile phone ratings using Term Frequency-Inverse Document Frequency (TF-IDF) features. We collected a dataset of over 13,000 mobile phone evaluations from the Flipkart website. The proposed method includes data purification, balancing, feature extraction from the TF-IDF, and model prediction using deep learning models. The proposed approach utilized other models such as Deep Neural Network (DNN), Long Short-Term Memory (LSTM), and Bidirectional LSTM to compare other classifiers. The experiments' outcomes demonstrate that the suggested model performs better than conventional deep learning methods regarding accuracy and efficiency. The GNN model achieved the best 99.0% accuracy rate. The proposed approach can help consumers make informed purchasing decisions and can be extended to other e-commerce platforms with large datasets of online reviews.

INDEX TERMS Flipkart smartphone rating, classification, deep learning, graph neural network, recommendation system, smartphone dataset.

I. INTRODUCTION

Customers frequently consult product reviews on websites like Amazon and Flipkart to decide whether a product is valuable before purchasing it. Reading reviews of recently released goods, examining poll data, and watching social media discussions can help brands understand what makes customers pleased or dissatisfied [1], [2], [3], [4]. Flipkart is one of the top online retailers selling various goods, including mobile phones (https://iide.co/case-studies/business-model-of-flipkart/#About Flipkart). The importance of consumer reviews in the decision-making process makes providing accurate product evaluations and reviews imperative. However, for a business like Flipkart, which has millions of products on its platform, gathering and analyzing customer feedback may take time and be resource-consuming.

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Sentiment analysis evaluates whether a given set of textual data is positive or negative in tone employing natural language processing (NLP) techniques [5], [6], [7]. It extracts subjective data from textual sources and evaluates text polarity. This functionality will be extremely useful for companies like Amazon, which value customer feedback and service reviews [8], [9], [10]. Customers provided feedback regarding the things they had purchased based on their experiences, contentment, thoughts, and opinions. End-user evaluations contain a large amount of unorganized information written in natural language [11], [12]. Even though it takes an extensive amount of effort, time, and financial resources to filter and analyze this many end-user evaluations manually, it is necessary to do so to find information that will be useful to new customers. To forecast the sentiment of each review, whether positive, neutral, or negative, utilizing different Machine Learning (ML) techniques, a sentimental evaluation and opinion mining-based strategy is employed to process the final assessments for a particular product. Recent ML and DL algorithm advancements have significantly improved text evaluation [13], [14].

The invention of AI has allowed researchers to delve extensively into textual material and derive new perspectives. A comprehensive examination of customer feedback and reviews is another tool brands may utilize to enhance their products [15], [16]. The motivation for this study is to support Flipkart's ratings and reviews of mobile phone manufacturers so that consumers can make better purchasing selections. Creating a deep learning model that can precisely predict mobile phone ratings based on consumer reviews is one of the objectives. Considering the primary and creative approach presented, the ratings and reviews system for mobile phones on Flipkart will benefit significantly. The corporation can increase the accuracy of its mobile phone ratings and reviews by using this strategy. Customers would be able to make better-informed purchase selections owing to the strategy. By offering a more reliable and effective rating and review system, this strategy can also aid Flipkart in setting itself apart from its rivals.

A. CONTRIBUTION

The research's primary contribution is described further down in the list form.

- This research contributes to recommendation systems-based mobile phone ratings classification by creating a new dataset for the Flipkart e-commerce platform. This dataset includes over 13,000 mobile phone reviews scraped from the website using web crawling techniques.
- This research utilizes deep learning models (DNN, LSTM, Bidirectional LSTM and GNN) for training the mobile phone rating classification model.
- This research uses data analysis techniques such as sentiment polarity distribution, label encoder and stemming for deep text analysis. It utilizes the TF-IDF for text processing and feature extraction from the reviews. This technique identifies the most important words in the reviews and assigns them weights based on their relevance to the rating prediction.
- The study assesses the model's effectiveness for categorizing mobile phone ratings using a variety of evaluation indicators. The outcomes show that the recommended method outperforms conventional DL models and successfully forecasts mobile phone ratings.

B. ORGANIZATION

The following describes the planned research methodology for Flipkart mobile rating classification: Section II contains a literature review on machine learning and deep learning techniques for categorizing Flipkart mobile ratings. The study technique for the proposed work, which utilizes data preprocessing, a deep learning model, and the Flipkart smartphone rating dataset, is described in Section III. Section IV discusses and explains the results and findings. Section V contains the work's conclusion and recommendations for additional investigation.

II. LITERATURE REVIEW

The literature on mobile phone rating and review systems emphasizes the significance of reliable assessments and evaluations in customers' decision-making. Several research investigations have examined various ML and DL methods for enhancing these systems' accuracy [1], [15], [17], [18], [19]. The importance of Amazon, Flipkart, and Snapdeal in today's digital market is undeniable. They are assisting in raising the share of sales that the e-commerce sector contributes to overall sales.

A. MACHINE LEARNING TECHNIQUES

Author in [1] provided the base work of this study to classify the sentiment of smartphone customers using active learning. They used various active learning-based machine learning classifiers for the evaluation. Their results showed that they achieved an accuracy of 91.49%. Authors in [2] investigate text and sentiment categorization techniques and methodologies for phone reviews on Amazon. The dataset we utilized for the study can be accessed on Kaggle and includes 60,000 reviews of 720 smartphones from different brands. Researchers combined ML and DL methods to achieve the same results, starting with basic logistic regression and naive Bayes models before progressing to sophisticated support vector machines and recurrent neural networks like LSTM utilizing the FastAI package. Authors in [20] offered an automated response analyzer. Moreover, provides an automated comment analyzer and categorization system that can efficiently use many ML technologies to detect the opposing perspectives of the customer comments gathered from Amazon and Flipkart data domains. In the research [21], customer reviews for mobile phone-related products were obtained through amazon.com to forecast the assessment of the product provided by the user reviews using sentimental analysis. A sentiment evaluation framework is proposed by [22] to categorize feedback on goods. It employs five well-known ML classifiers to identify the most effective classifier: NB, SVM, DT, KNN, and Maximum Entropy. The Kaggle site was the source of the 82,815 reviews that comprise the dataset. Maximum Entropy and NB function better than the other predictors in terms of accuracy across every test, according to the findings. In [10], authors use ML techniques such as LR, SGD, NB, and CNN to forecast customer sentiment through smartphone ratings. The trials showed that the optimal outcomes for the dataset's imbalanced and balanced variants are obtained using CNN with the word2vec strategy. Authors in [23] focused on collecting aspect keywords from tweets employing NLTK techniques, which presents a challenge in multi-aspect retrieval. Machine learning techniques that may be trained on supervised methodologies are also used to anticipate and classify the sentiment contained in tweets posted from mobile devices.

B. DEEP LEARNING TECHNIQUES

Authors in [19] developed a deep learning-based method for analyzing the sentiment in user evaluations of mobile phones. They employed a Convolutional Neural Network (CNN) and a Bidirectional Long Short-Term Memory (BiLSTM) model to predict the sentiment of mobile phone ratings. The outcomes demonstrated that the suggested method performed better in accuracy than conventional machine learning methods. To assist consumers in making decisions, the authors in [24] developed an automated SentiDecpective technique that categorizes end-user evaluations into positive, neutral, and negative feelings and identifies misleading crowd-users rating data on the social networking site. The suggested sentiments approach yields positive results for detecting consumer feelings from online user feedback, obtaining an average of 94.01% precision, 93.69% recall, and 93.81% F-measure value for categorizing positive sentiments using various ML algorithms. Authors in [25] suggested a deep learning solution to address a common issue on e-commerce websites where the user's feedback does not complement the rating. Before developing their model, the authors learned the syntactic and semantic linkages of a "review text" using article matrices. Further groups and kinds of review embedding are made to create a product sequence given to a Recurrent Gated Unit (GRU) to train product embedding. Concatenating comment integrating from article vectors with product embedding derived from GRU allows an SVM to be trained for sentiment categorization. Utilizing only review embedding, the classifier obtains an accuracy of 81.29%. When product integration is factored, the accuracy increases to 81.82%. Authors in [26] examined DL-based techniques for assessing sentiment on social networks. It begins by outlining the single-modal sentiment assessment procedure on social media. After that, it provides an overview of social media's multimodal sentiment evaluation techniques and categorizes them into three groups based on distinct fusion strategies: feature layer fusion, decision layer fusion, and linear regression approach. To solve sentiment assessment issues, a novel method involving data collection, processing, feature-encoded data, and categorization using three long short-term memory variants is provided in a study [27]. The studies employed various textual datasets to assess the significance of the proposed models. The suggested method of sentiment prediction yields more accurate, or at least equivalent, outcomes with less computing work.

In summary, various methods are suggested for predicting mobile ratings based on machine learning and deep learning algorithms. They should have considered feature selection and extraction approaches; hence, they are still constrained in providing greater performance. This research suggested a practical method based on DL models to classify mobile phone ratings. Flipkart leverages the collective intelligence of its users to improve the accuracy of its ratings and reviews. Finally, it can shorten the time and computational resources needed to train an ML model, making it a more effective strategy.

III. PROPOSED METHODOLOGY

The proposed approach used data from Flipkart to create a predictive algorithm that precisely predicts the ratings of mobile phones sold on Flipkart. The suggested method includes several steps, including dataset construction, data cleaning and preprocessing, data balance, feature extraction, and model prediction utilizing DL models. The proposed approach is shown in Figure 1.

In the first stage, data is extracted from Flipkart's website using a web spider or web crawler. The product name, brand, price, rating, and reviews are merely examples of the essential data the spider intends to retrieve. Next, preprocessing and cleaning are required for the extracted data because they contain errors or inconsistencies. At this stage, duplicates are eliminated, errors are fixed, and data is transformed into a standardized format. During this phase, the data are balanced by either oversampling the minority class or undersampling the majority class. Additionally, unbalanced data can impair the efficacy of the prediction model. A TF-IDF vectorizer transforms textual data, such as reviews, into numerical vectors. This method finds critical words in reviews to forecast a product's rating. The TF-IDF vectors ultimately train a deep-learning model. This algorithm is employed to forecast customer reviews on new smartphones offered by Flipkart. Extracting and preprocessing data from Flipkart, balancing the data, identifying pertinent features, and training a deep learning model to forecast the ratings of mobile phones sold on Flipkart are all steps in the proposed strategy.

A. EXPERIMENTAL DATASET

Customers' reviews and opinions on various mobile phones were collated through Flipkart. Using these reviews, a model may be trained to forecast how people evaluate various mobile devices. This study produced a dataset for detailed

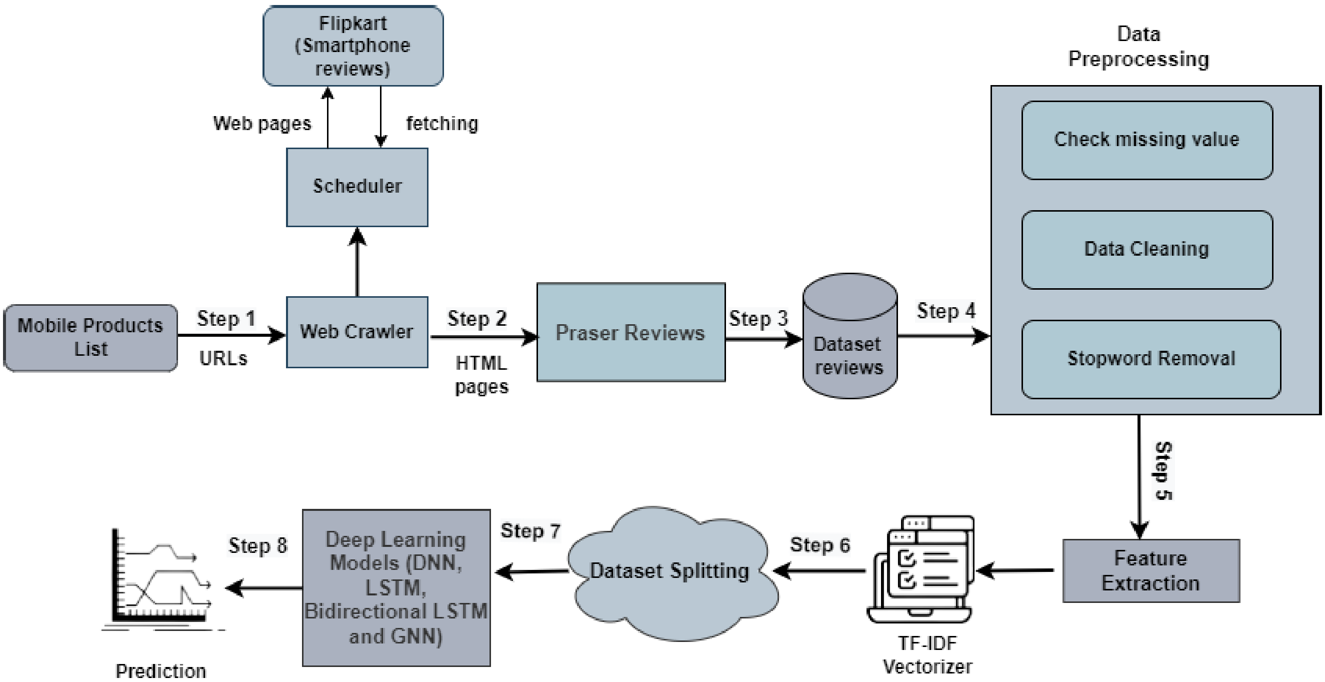


FIGURE 1. Proposed approach for mobile rating prediction.

TABLE 1. Description of dataset features.

Features	Description
product_id	A unique product id
product title	Name of the mobile device used by the reviewer
rating	Ratings provided by the customer
summary	Reviews summary
review	Reviews given by the customer
location	Location of customer
date	Date on which customer gives the review
upvotes	Upvotes given by the customer
downvotes	Down votes given by the customer

user research and forecasts regarding specific mobile devices. The data set was gathered by crawling down to the site's database (more than 13,000 smartphone reviews) on the website "Flipkart.com" with a crawler (or bots). The data was crawled within 10 months (May 2022 to March 2023). The scheduler was implemented to ensure the crawling procedure is effective, considerate of the website's policies, and able to cope with changes in the website's structure over time. The final dataset has 13,589 rows and 9 features. Table 1 explains each attribute.

B. DATA PREPROCESSING

The data preparation stage is essential to produce more accurate data and improve the model's performance. In this section, data preprocessing is applied using Exploratory Data Analysis (EDA), converting the categorical data into integer values, cleaning, deep text analysis, splitting the data, and balancing the data with SMOTE. This paper uses stemming and TF-IDF vectorizer for feature extraction.

1) EXPLORATORY DATA ANALYSIS

EDA is significant to the conduct of all research. The fundamental goal of the exploratory analysis is to test the hypothesis; therefore, identifying outliers and abnormalities in the data is essential. It also provides tools for analyzing and visualizing the data, generally through graphical representation, to form hypotheses. After data collection, EDA is carried out. The data is effectively observed, displayed, and updated without making assumptions to evaluate the data quality and create models [28].

We remove the missing values from the "location" and "review" variables to preprocess the Flipkart dataset. Following that, the textual data is cleaned using various text preparation techniques. To accomplish this, the "Review" and "summary" columns must be consolidated into one column, and all punctuation and characters with unclear names must be eliminated. In addition, we expand words that have short forms (e.g., "won't" to "will not"). Additionally, we eliminate phrases like "no," "nor," and "not" from the stop words list. Finally, we substitute any "//" occurrences with a space. These steps aid in standardizing textual data, removing noise and irrelevant information, and establishing datasets for feature extraction and model training.

Preprocessing the Flipkart dataset involves several steps that clean and standardize the textual data. This study initially removes 11 missing values from the "review" element and 95 missing values from the "location" property to ensure the dataset is complete. Several text preprocessing procedures were then used in this study to clear the textual content. We removed all punctuation from the text, including commas, periods, and question marks, to reduce the dimensionality of the dataset and eliminate noise. We also eliminate any characters whose names are unclear because they do not contribute to the text's meaning. We concatenate the "Review" and "Summary" columns into a single string to merge them into a single column. This procedure facilitates feature extraction by reducing the number of columns in the dataset.

The expansion of words that incorporate short forms is another crucial preprocessing step. We change words like "won't" to "will not," "can't," to "cannot," and so forth. This makes the syntax more consistent and reduces uncertainty when evaluating the data. We also eliminate words like "no," "nor," and "not" from the stop words list, as these words do not contribute anything to the overall meaning of the text. The dimensionality of the dataset is decreased by removing these terms, which facilitates the extraction of useful features. Finally, we substitute a space for "//" occurrences. In this stage, any excess characters that might have been added throughout the crawling process are removed. In the next step, we create the "sentiment" column. This crucial preprocessing stage determines the outcome column (reviewer's sentiment) based on the final score. If the score is greater than 3, we consider it positive; if it is lower than 3, we consider it negative. If the result is 3, we consider it to be neutral. In the next step, more features are created for text analysis to create polarity, review length and word count. We use Textblob to figure out the rate of sentiment. It is between $[-1,1]$ where -1 is negative, and 1 is positive polarity. It determines the length of the review, which includes each letter and space and measures the word length.

2) SENTIMENT POLARITY DISTRIBUTION

The next phase in the preprocessing is to check the sentiment polarity distribution. By examining the polarity distribution, we observe that there are far more positive polarities than negative ones. This polarity distribution guarantees the quantity of positive ratings we obtain. This polarity can be described as regularly distributed but not as conventional normal. Figure 2 depicts the pie chart for polarity distribution.

Before we build the model for our sentiment analysis, we must convert the review texts into vector formation, as a computer cannot understand words and their sentiment. This project used stemming and TF-TDF methods to convert the texts.

3) STEMMING

Stemming reduces a word to its base or root form. Stemming aims to normalize words so that different forms of the same word can be treated as a single term. For example, the words "running" and "run" have the same stem, which is "run". Applying stemming can convert both words to their common stem, making them equivalent for information retrieval.

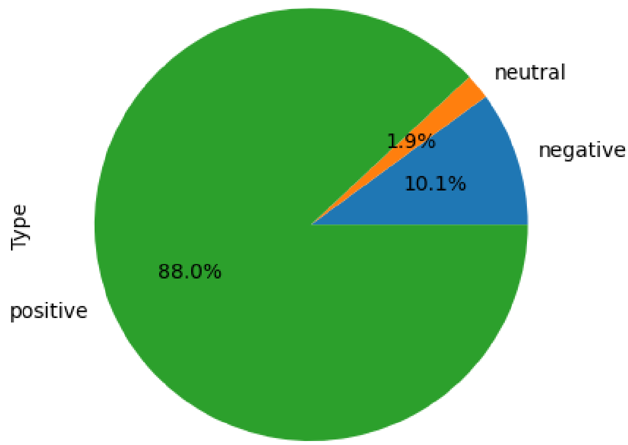


FIGURE 2. **Sentiment polarity distribution.**

4) FEATURE EXTRACTION

Term Frequency-Inverse Document Frequency (TF-IDF) is a statistical measure used to evaluate the relevance of a term in a document relative to a corpus of documents. TF-IDF is calculated by multiplying two values: the term frequency (TF) and the inverse document frequency (IDF). The term frequency measures how often a term appears in a document, while the inverse document frequency measures how important a term is across a corpus of documents.

In this research for Flipkart feature extraction, the TF-IDF feature vectorizer is used to extract important keywords from the product description or reviews. We have a corpus of product reviews for a certain category of products, and we need to extract the most important features for each product. Assume that the product review is a document and apply the TF-IDF algorithm to compute the scores for each word in the corpus. The resulting feature vector for each product contains the top N words with the highest TF-IDF scores that can be used as features to represent the product. In this research, the mathematical equation 2 for computing the TF-IDF score for a word w in document d is:

$$Tf - IDF(w, d) = TF(w, d) \times IDF(w) \tag{1}$$

where T F(w, d) is the term frequency of word w in document d, and IDF(w) is the inverse document frequency of word w in the corpus. The IDF is computed in equation 2:

$$IDF(w) = \frac{logN}{nw} \tag{2}$$

N is the total number of documents in the corpus, and nw is the number of documents containing the word w.

The Flipkart dataset for upsampling the minority class used a resampling technique to create additional samples from the existing data. This technique involves creating synthetic samples from the minority class by randomly selecting observations and adding small variations to the data to create new data points. The upsampling process helps balance the dataset's class distribution and improves the machine learning model's performance. By creating additional samples from the minority class, we can ensure that the model is not biased towards the majority class and can make accurate predictions for both classes [29], [30], [31]. The proposed work splits the dataset into training and testing sets to apply the resampling technique. Then, use the resampling technique on the training set to create a new, balanced dataset. Finally, this research used the new dataset to train the deep learning model.

C. DEEP NEURAL NETWORK MODEL

A Deep Neural Network (DNN) is a kind of Neural Network (NN) that consists of multiple layers of interconnected nodes or artificial neurons. Its purpose is to model patterns and relationships found in data. DNNs are a subset of networks. They are characterized by their depth, meaning they have more than one hidden layer between the input and output layers. These hidden layers allow DNNs to grasp data representations and handle tasks like natural language processing, among others [32].

D. LONG SHORT TERM MEMORY

LSTMs, also known as long short-term memory networks, were developed to overcome the vanishing gradient problem commonly encountered in RNNs and effectively capture long-range dependencies in data. LSTMs are especially useful for tasks that involve time series data and natural language processing [33].

E. BIDIRACTIONAL LSTM

A Bidirectional Long Short Term Memory (BiLSTM) is a type of network that extends the capabilities of the LSTM network. Unlike the LSTM, which only processes input sequences in one direction, the BiLSTM processes them in both backward directions. This unique feature enables the network to capture dependencies simultaneously from past and future time steps [34].

F. GRAPHICAL NEURAL NET MODEL

A Graph Neural Network (GNN) is an architecture created to handle and represent data in graphs or networks. In this context, graphs are composed of nodes (also called vertices) interconnected by edges (or links). GNNs are employed to acquire knowledge and extract insights from data [35], [36].

The proposed approach for mobile rating prediction on Flipkart is presented as an Algorithm 1. The algorithm inputs Flipkart's data and returns predicted mobile phone ratings as output. The algorithm has three main functions: CreateDataset, TrainModel, and PredictRatings. The Main function integrates the three functions to form the complete prediction system. The CreateDataset function uses a web spider to extract relevant information such as product name, brand, price, rating, and reviews from Flipkart's website.

WSP is the web spider equation, which calculates the sum of all the relevant information extracted by the web spider from Flipkart's website. The retrieved data is then cleaned and

Algorithm 1 Proposed Approach for Mobile Rating Prediction on Flipkart

Input: *Flipkart Data*
Output: *Mobile phone rating prediction*
function CreateFlipkartDataset
$WSP = \sum_{i=1}^{n} Pi$ c Using WebSpider to retrieve information
D_p = Data Preprocessing
DA = Data Analysis
Identify missing values
Data cleaning
Stopwords removal
F_e = Feature Extraction
$Tf - IDF(w, d) = TF(w, d) \times IDF(w)$ TF-IDF vectorizer
SM = smote() Balance Data
return x, y
function TrainModel (x, y)
$Splitting = x\_train, x\_test, , y\_train, y\_test$
ML = Create Deep learning Model
$DNN()$ = Deep Neural Net
$LSTM()$ = Long Short Term Memory
$BiLSTM()$ = Bidirectional LSTM
GNN = Graphical Neural Network
return *model*
function RatingPrediction $(model)$
$E_m \leftarrow$ Accuracy, Precision, Recall, F1-Measure
Return $\leftarrow$ predicted result

preprocessed by removing duplicates, correcting errors, and converting it to a standardized format. Textual data, such as reviews, are converted to numerical vectors using the TFIDF vectorizer. The data is balanced by oversampling the minority class using SMOTE. $TF-IDF(t, d)$ is the TF-IDF equation, which converts the textual data into numerical vectors that can be fed into the DL model for training a prediction. T F(t, d) is the term frequency, the frequency of a term t in document d. IDF(t) is the inverse document frequency, which measures the rareness of a term t across all documents in the dataset. Finally, the function returns the preprocessed dataset as x and y.

The TrainModel function trains a DL model on the preprocessed dataset. The data is divided into 25% and 75% for testing and training, respectively. Finally, the function returns the trained model. The PredictRatings function uses the trained model to predict the ratings of new mobile phones sold on Flipkart. The function takes the trained model and preprocessed dataset as input and returns the predicted ratings as output.

The Main function integrates the CreateDataset, TrainModel, and PredictRatings functions to form the complete prediction system. The function first collects mobile phone data from Flipkart's website. The CreateDataset function is then called on this data to preprocess and divide it into two clients for machine learning. The TrainModel function is called on the preprocessed dataset to train the ensemble voting model. Finally, the PredictRatings function is called on the trained model and preprocessed dataset to predict the ratings of new mobile phones sold on Flipkart. The function returns the predicted ratings as output.

G. EVALUATION METRICS

The effectiveness of the suggested model is assessed using the evaluation metrics listed below. The accuracy reported in Equation 3, the precision in Equation 4, the recall in Equation 5, and the F1-score in Equation 6 are some of the metrics used to evaluate the prediction and classification issues.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{3}$$

$$Precision = \frac{TP}{TP + FP} \tag{4}$$

$$Recall = \frac{TP}{TN + FN} \tag{5}$$

$$F1 - score = 2 \times \frac{Precision + Recall}{Precision + Recall} \tag{6}$$

A confusion matrix is a table used to evaluate the performance of a classification model by comparing its predicted outputs with the actual outputs. It is often used in machine learning to measure the effectiveness of a classification model. A confusion matrix typically has four quadrants, each representing a possible outcome: True Positive (TP), False Positive (FP), True Negative (TN) and False Negative (FN). The matrix rows represent the actual class labels, while the columns represent the predicted ones. The matrix's main diagonal represents the correctly classified instances, while the off-diagonal elements represent the misclassified instances. These metrics help identify the model's strengths and weaknesses and can be used to improve the model to achieve better results.

IV. RESULT AND DISCUSSION

The experimental results and discussion for the classification of Flipkart dataset rating using a deep learning model with TF-IDF vectorizer features are explained in this section. The dataset was split into 20% for model testing and 75% for model training. The model's performance was evaluated using various evaluation metrics. The results obtained from the experiments are discussed in detail in this section.

A. DEEP NEURAL NET MODEL

Table 2 exhibits the categorization performance results for a DNN model. The model is 81% accurate, as shown in the table. Class 0 has a precision and recall of 0.74 and 0.53, respectively. Accordingly, the model successfully identified class 0 in 74% of the instances while correctly identifying class 0 in 53% of the instances overall. Precision and recall for class 1 are 0.80 and 0.15, correspondingly. This indicates that just 15% of all cases were classified as class 1 by the model, even though it correctly identified 80% of instances as belonging to that class. For class 2, the precision and recall are 0.82 and 0.94, respectively. This indicates that the model accurately classified 82% of the occurrences of class 2, and 94% of all instances of class 2 were accurately categorized. Averaging across all classes, the macro average values have an F1-score of 0.58, precision of 0.79, and recall of 0.54. The Weighted average values offer a weighted mean with precision of 0.80, recall of 0.81, and F1-score of 0.79 while considering distributions of classes. The DNN model has decent accuracy overall but has lower precision and recall for the less common classes (classes 1 and 2).

TABLE 2. Result of DNN model.

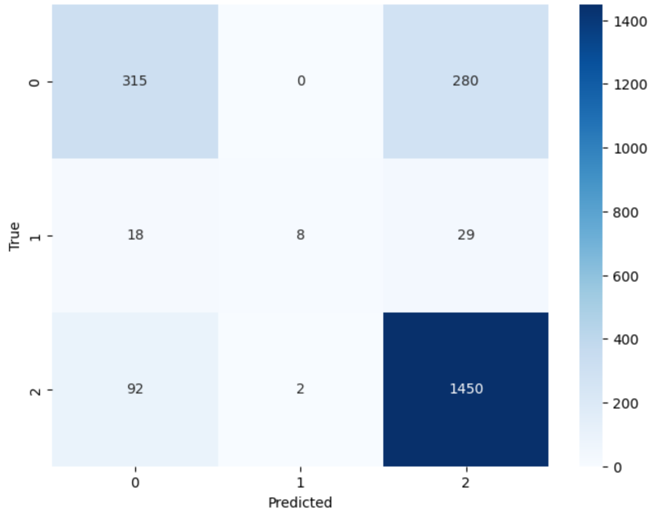
Classes	Precision	Recall	F1-score	Support
0	0.74	0.53	0.62	595
1	0.80	0.15	0.25	55
2	0.82	0.94	0.88	154
Accuracy	-	-	0.81	2194
Macro Avg	0.79	0.54	0.58	2194
Weighted Avg	0.80	0.81	0.79	2194

The confusion matrix of the DNN model is visualized in Figure 3a. It gives a high-level understanding of a classification algorithm's execution. It performs better since the proposed method has fewer false positive and negative outcomes and greater continuous, better true positive and negative values. The confusion matrix shows that the algorithm erroneously classifies the remaining records while the diagonal members are correctly predicted. Figure 3b indicates the Receiver Operating Characteristic (ROC) curve. The blue line indicates the ROC curve area of 0.89 for Class 0, the orange line represents the ROC curve with a 0.83 value for Class 1, and the green line with 0.88 exhibits Class 2.

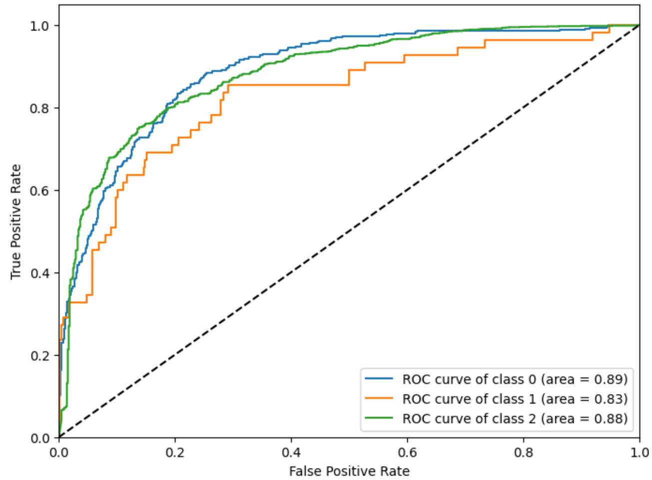
The performance assessment of the DNN model with training and validation loss and accuracy is shown in Figure 4. The training accuracy is 0.825, and the validation accuracy is 0.80 every 20 epochs. Similarly, the training loss is 2.0, and the validation loss is 1.15.

B. LONG SHORT TERM MEMORY (LSTM)

Table 3 presents the categorization task outcomes of an LSTM model. The model could accurately categorize 97% of the data after being trained on 2194 data points. The precision is 0.97 for class 0, 0.70 for class 1, and 0.98 for class 2. The recall for class 0 is 0.97; for class 1, it is 0.69; for class 2, it is 0.98. The F1-score for class 0 is 0.97, for class 1 is 0.70, and for class 2 is 0.98. The amount of instances for each class is indicated by support. There are 595 examples of class 0, 55 instances of class 1, and 1544 instances of class 2, respectively. The macro average for precision, recall, and F1-score is 0.88, and the weighted average for these three variables is 0.97. The approach works effectively, particularly for classes 0 and 2. The performance indicators for Class 1 are marginally lower.

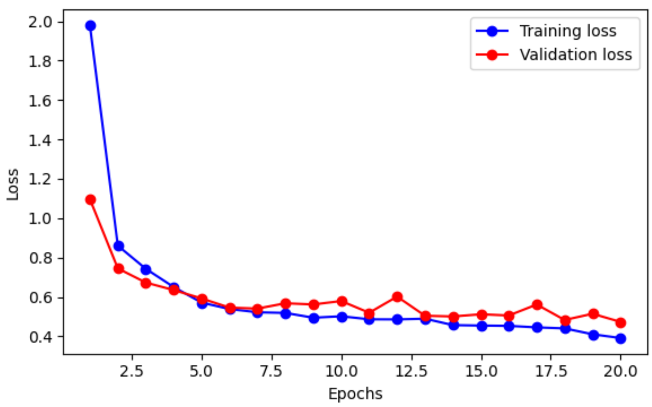


(a) Confusion Matrix of DNN Model



(b) ROC Curve of DNN Model

FIGURE 3. Visualization of DNN model results.



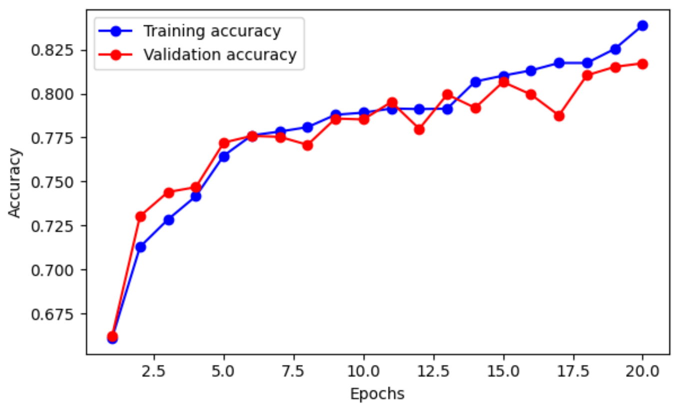


FIGURE 4. Performance of DNN model.

TABLE 3. Result of LSTM model.

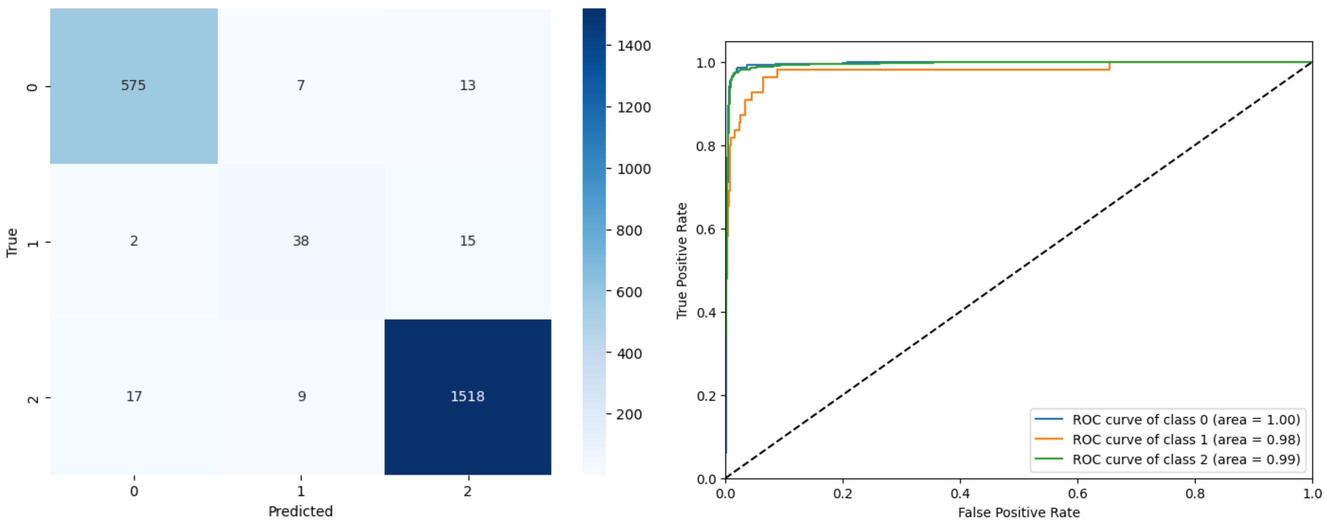
Classes	Precision	Recall	F1-score	Support
0	0.97	0.97	0.97	595
1	0.70	0.69	0.70	55
2	0.98	0.98	0.98	1544
Accuracy	-	-	0.97	2194
Macro Avg	0.88	0.88	0.88	2194
Weighted Avg	0.97	0.97	0.97	2194

The confusion matrix of the LSTM model is demonstrated graphically in Figure 5a. It gives a summary of the execution of a classification algorithm. The proposed technique performs better because it has more continuous, better true positive and negative values and fewer false positive and negative values. The confusion matrix shows that the algorithm erroneously classifies the remaining records while the diagonal members are correctly predicted. Figure 5b indicates the Receiver Operating Characteristic (ROC) curve. The blue line indicates the ROC curve area of 1.00 for Class 0, the orange line represents the ROC curve with a 0.98 value for Class 1, and the green line with 0.99 exhibits Class 2.

Figure 6 illustrates the performance evaluation of the LSTM framework with training and validation loss and accuracy. The training accuracy is 0.95, and the validation accuracy is 0.96 for every 7 epochs. Similarly, the training loss is 0.7, and the validation loss is 0.45.

C. BIDIRECTIONAL LSTM MODEL

Table 4 displays the results of a bidirectional LSTM model applied to a 3-class classification issue. The weighted F1-score and total accuracy of the model are both 97 percent. The model scored exceptionally well in the majority class (class 2), achieving a precision, recall, and F1 score of 100%. However, it also did well in the minority classes



(a) Confusion Matrix of LSTM Model (b) ROC Curve of DNN Model

FIGURE 5. Graphical visualization of LSTM model results.

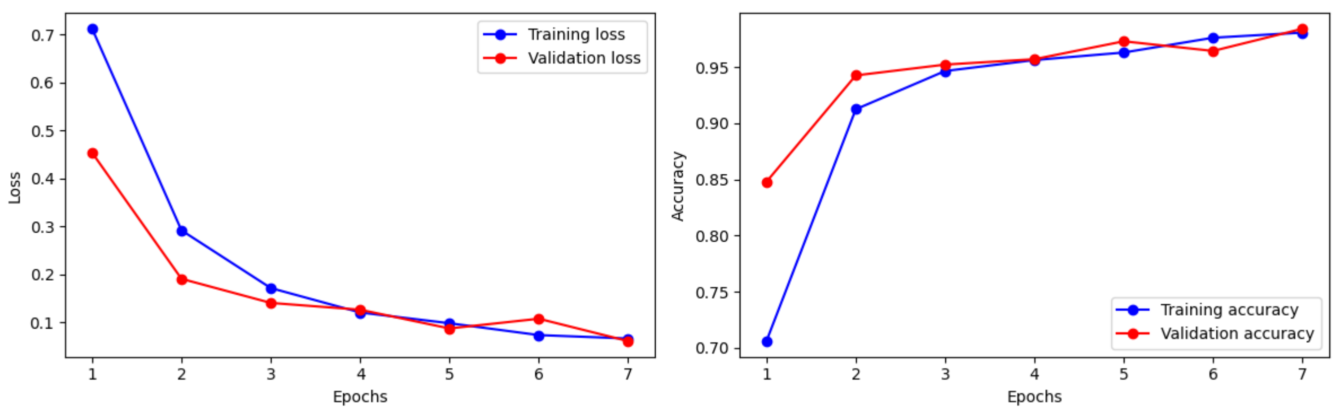


FIGURE 6. Performance of LSTM model.

TABLE 4. Result of bidirectional LSTM model.

Classes	Precision	Recall	F1-score	Support
0	0.96	0.98	0.97	595
1	0.70	0.80	0.75	55
2	0.99	0.98	0.98	1544
Accuracy	-	-	0.97	2194
Macro Avg	0.88	0.92	0.90	2194
Weighted Avg	0.98	0.97	0.97	2194

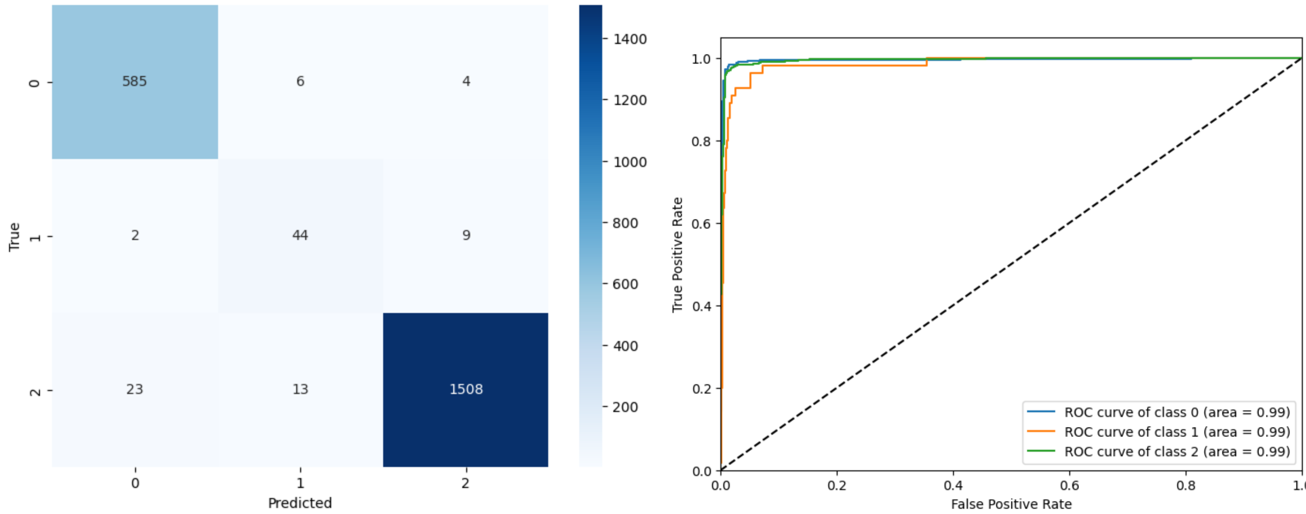
(classes 0 and 1), with precision, recall, and F1-scores of 0.96, 0.98, and 0.97 for class 0 and 0.70, 0.80, and 0.75 for class 1, respectively. The bidirectional LSTM model demonstrated its capacity to learn complicated associations in sequential data by achieving extremely good overall results on this classification assignment.

Figure 7a visualized the confusion matrix of the Bidirectional LSTM framework. It gives a general overview of how a classification algorithm operates. The suggested strategy operates better because it has fewer false positive and negative outcomes and more continuous, superior actual positive and negative outcomes. The confusion matrix demonstrates that while the program correctly anticipates the diagonal components, it labels the other data inaccurately. Figure 7b indicates the Receiver Operating Characteristic (ROC) curve. The blue line indicates the ROC curve area of 0.99 for Class 0, the orange line represents the ROC curve with a 0.99 value for Class 1, and the green line with 0.99 exhibits Class 2.

Figure 8 illustrates the performance evaluation of the Bidirectional LSTM model incorporating training and verification of loss and accuracy. The training accuracy is 0.975, and the validation accuracy is 0.96 for every 7 epochs. The training loss is 0.6, and the validation loss is 0.21.

D. GRAPH NEURAL NETWORK MODEL

The outcomes of a GNN model on a classification job with three classes are displayed in Table 5. The model obtains a very high overall accuracy of 99%. The model can correctly classify data points from all classes for each class. Class 0 has an F1-score of 0.99, a precision of 0.98, and a recall of



(a) Confusion Matrix of Bidirectional LSTM Model

(b) ROC Curve of Bidirectional LSTM Model

FIGURE 7. Graphical visualization of bidirectional LSTM model results.

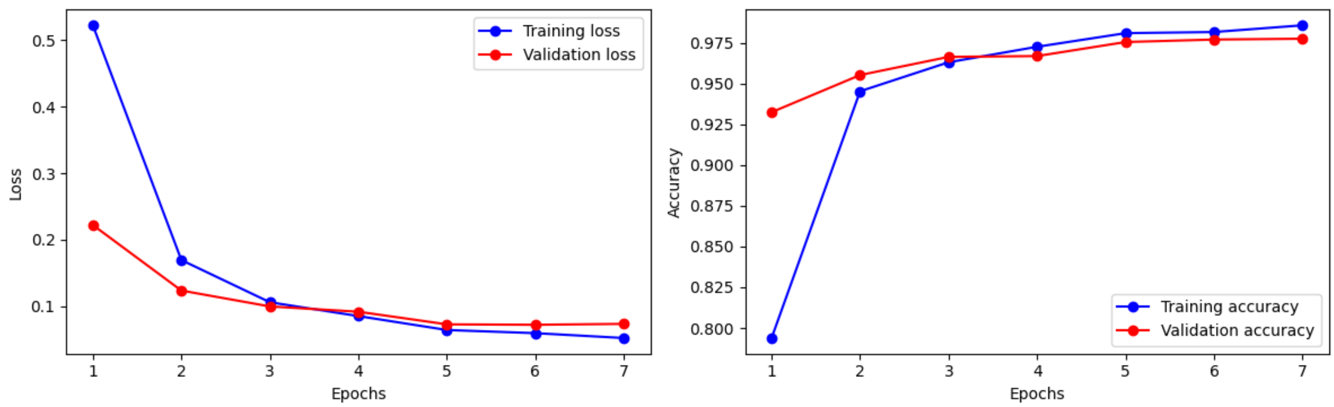


FIGURE 8. Performance of bidirectional LSTM model.

TABLE 5. Result of GNN model.

Classes	Precision	Recall	F1-score	Support
0	0.98	0.99	0.99	595
1	0.96	0.89	0.92	55
2	1.00	0.99	0.99	1544
Accuracy	-	-	0.99	2194
Macro Avg	0.98	0.96	0.97	2194
Weighted Avg	0.99	0.99	0.99	2194

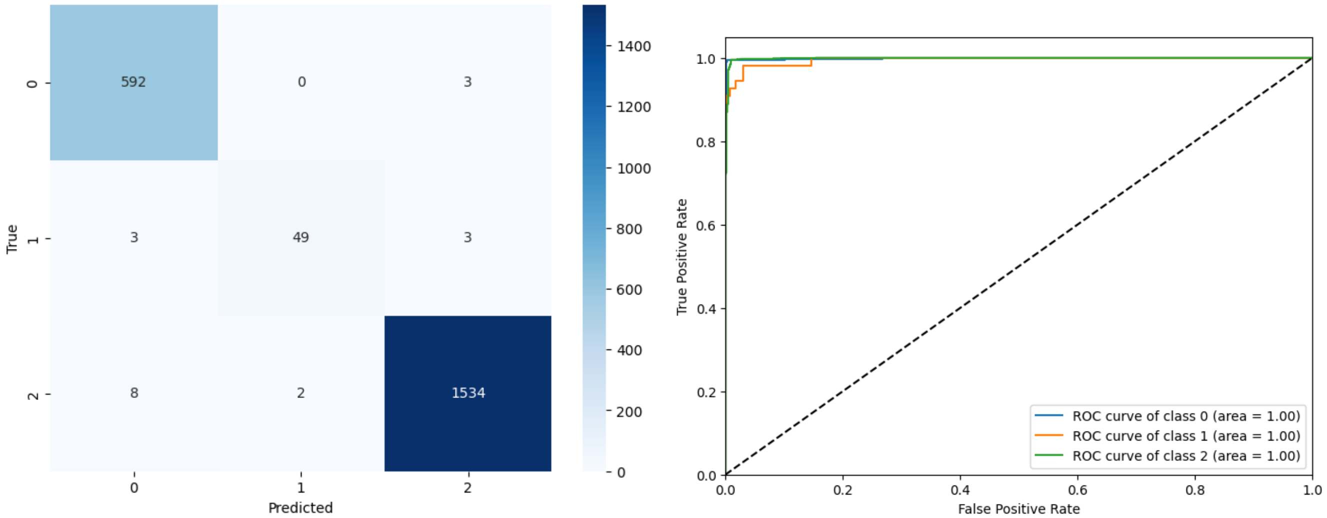
0.99. Precision, recall, and F1-score for Class 1 are all 0.96, 0.89, and 0.92 respectively. Class 2 has an F1-score of 0.99, a precision of 1.00, and a recall of 0.99. Overall, the GNN model excels at this classification function.

The confusion matrix of the GNN model is graphically visualized in Figure 9a. It provides a broad explanation of how a categorization algorithm functions. The suggested strategy functions better because it has fewer false positive and negative results and more continuous, improved actual outcomes. The confusion matrix reveals that while the diagonal elements are properly anticipated, the program incorrectly classifies the other records. Figure 9b demonstrates the Receiver Operating Characteristic (ROC) curve. The blue line indicates the ROC curve area of 1.00 for Class 0, the orange line represents the ROC curve with a 1.00 value for Class 1, and the green line with 1.00 exhibits Class 2.

Figure 10 exhibits the performance evaluation of the GNN model, including training and validation loss and accuracy. The training accuracy is 0.99, and the validation accuracy is 0.96 for every 10 epochs. Similarly, the training loss is 0.27, and the validation loss is 0.11.

V. DISCUSSION AND ANALYSIS

The proliferation of internet reviews and the rise in mobile phone usage have given customers opportunities and difficulties. The experiment indicates that the suggested model functions well on the Flipkart dataset. The performance of the proposed model is evaluated using the optimization essential



(a) Confusion Matrix of GNN Model

(b) ROC Curve of GNN Model

FIGURE 9. **Graphical visualization of GNN model results.**

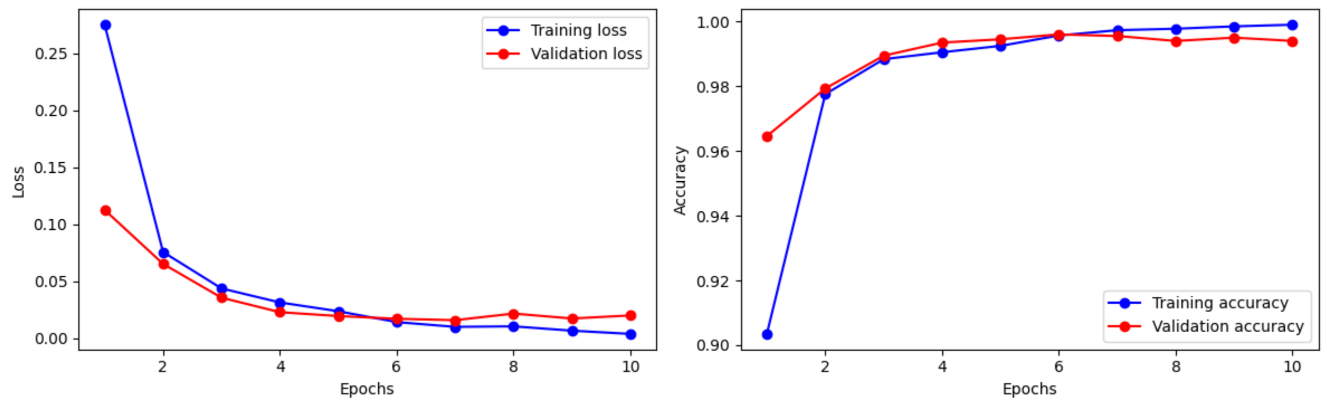


FIGURE 10. **Performance of GNN model.**

metrics of Accuracy, Precision, Recall, and F1-measure to perform the statistical analysis. Statistical analysis evaluates the performance, generalization potential, and importance of deep learning models' outcomes. The degree of intricacy and complexity in a DL model's structure and its capacity to recognize patterns and relationships in the data are called the model's complexity. A DL model's architecture uses several parameters (weights and biases) to determine its level of complexity. A model becomes more sophisticated as more parameters are added to it. A network's parameters increase with the number of layers and neurons. While allowing deep learning models to recognize complex patterns in data, parameter diversity also necessitates a large amount of processing power. Complex models can capture intricate correlations in the data, but if they are not appropriately regularised, they are also more susceptible to overfitting. Regularisation methods like dropout, weight deterioration, and batch normalization are frequently used to mitigate this, which increases the model's complexity.

Various approaches Include penalty terms to the loss function, and regularisation can lower model complexity. Discouraging extremely complex parameter values helps prevent overfitting. Deep Learning models (DNN, LSTM, Bidirectional LSTM and GNN) can increase the prediction performance. This study uses deep learning models to address mobile phone ratings classification issues. The experimental findings demonstrate that the suggested deep learning model outperforms traditional methods regarding accuracy and efficiency. The test results demonstrate that the proposed model is more effective than alternative mobile phone rating prediction methods.

VI. CONCLUSION

Flipkart has quickly risen to prominence as one of the most popular online marketplaces because of having one of the broadest product options in the sector, including mobile phones. Nevertheless, a company like Flipkart, which has millions of products on its website, may need to invest time and effort in gathering and analyzing customer feedback. This research proposes a Flipkart mobile rating classification approach using deep learning models. The proposed approach utilized a DNN, LSTM, Bidirectional LSTM, and GNN models for classification. This study developed a unique dataset for classification and employed a web spider to gather pertinent data from Flipkart's website. The data was then preprocessed by removing duplicates, fixing mistakes, and standardizing the format. The approach uses the TF-IDF vectorizer to convert textual data into numerical vectors and trains an ensemble voting model using machine learning to predict mobile phone ratings on Flipkart. This study produced an extensive dataset for the detailed examination and forecasting of mobile phone ratings. The suggested method offers precise and effective ratings for new mobile phones on Flipkart. One drawback is the scalability of the approach. The suggested method only applies to the dataset of mobile phone reviews gathered from the Flipkart website. The approach might need to be adjusted or updated to handle larger datasets and different kinds of products. In the future, we intend to employ more Natural Language Processing (NLP) methods besides TF-IDF, including topic modeling or word embeddings. Future research would use a combination of extraction and ensemble deep learning models to study the performance of the suggested approach. Furthermore, to increase the model's accuracy, the suggested method could include extra features, like the user's demographic data or the product's specifications.

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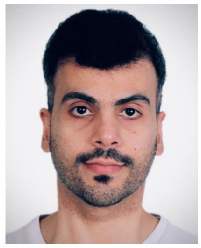

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