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Abstract. Banking has become an integral part of our lives. Fintech (Financial Technology) skyrocketed the number of people willing to use Mobile Financial Services (MFS) for their daily financial transactions. The banks are providing their services via mobile applications, which can be found on the Google Play Store. These Mobile Financial Services (MFS) provide mobility and increase efficiency by 10-fold. With an astonishing number of users came an abundant number of reviews for these apps. User reviews are the backbone of an application's success. They provide information about hands-on experience. This study mainly focuses on the reactions of the users of such apps. Sentiment analysis is being used to draw out emotions from the users based on their written reviews. The primary goal of this paper is to examine the points of view of such application users. A total of 5414 pieces of data were collected from the Google Play Store and classified as negative, neutral, or positive. The data model has been evaluated using CNN, LSTM, and BiLSTM algorithms. Compared to CNN and LSTM, the BiLSTM algorithm produced the best model with an accuracy of 97.07%.

Keywords: FinTech, Mobile Financial Service, Sentiment Analysis, LSTM, CNN, BiLSTM, Glove, Text Classification.

1 Introduction

The term "Banking" dates back to 1,800 BC. The concept of a bank revolved around loaning money and making a profit on personal assets. But the modern definition of a bank hadn’t been invented until the 17th century. With this revolutionary invention, the face of the world changed significantly. From that point on, banks have become an integral part of our way of life [2]. With its importance and necessity only growing over time, newer and easier ways of banking came into being. One of these modern inventions is the concept of Mobile Financial Service (MFS). Mobile Banking is commonly defined as a service that is provided by financial institutions, for instance, banks, trust corporations, and insurance companies, so that a user can remotely access and perform financial transactions via a mobile device [3]. Lately, there has been a huge spike in the usage of MBA (Mobile Banking Application) by the common folk of Bangladesh. More and more people are utilizing mobile banking. With overall good services and user-friendly interfaces, the MBA (Mobile Banking Application) has changed the traditional way of banking. Over the years, numerous Mobile Banking Applications have been developed right here in Bangladesh. Apps such as bKash, Sure Cash, Upay, Nagad, Rocket, Nexus Pay, and Tap have become extremely popular among the masses. Because of the competitive nature of this field of banking, most MBA (Mobile Banking Applications) provide a unique experience to their users [4]. Urbanization, development, and the fact that smart mobile devices have gone mainstream and are more available to the commoners are a few reasons why MFS (Mobile Financial Service) has gained so much traction in Bangladesh. More than 180 million users and Tk 89,169 crore worth of transactions have made this field of business a force to be reckoned with. The number of users and transactions is only growing exponentially, with no indication of slowing down [5]. As the number of these applications and services grows, so does the confusion among the masses. With so many services to choose from, one can easily get swept up by a less desirable service without even knowing. To solve such an issue, the emotions classifier (Negative, Neutral and lastly Positive) has been invented. By using text analysis, one can classify the emotions provided by the users. This technique is known as sentiment analysis. After combining numerous algorithms in a sequential manner of events, we can solve complex issues. By utilizing their vigorous algorithm sequences, neural networks can autocorrect in deep learning. The most accurate results can be obtained by using deep learning structures to break down documents, phrases, and paragraphs into individual segments. This is supplementarily sufficient and probable compared to conventional natural language processing algorithms [1]. Because of the abundance of MBA (Mobile Banking Application) on the Google Play Store, we are attempting to initiate deep learning procedures to extricate the sentiment of these service users. We have used Deep Learning methods and algorithms such as CNN, LSTM, and BiLSTM for our study. As the reviews provided by the users are valuable to both service providers and customers, we are aiming to get an eccentric point of view from the application users.

Table 1. Dataset sample.

Class	Sentences
Positive	This app helps a lot in our day-to-day problems. One solution is the bkash app. Thanks to all the founding members and those brilliant minds who worked hard to build this.
Negative	What the heck? How the heck a banking system can be as buggy like this. Billing doesn't work most of the time. Edu payment doesn't work most of the time. App doesn't load anything. Unreliable service. And all these after the most charges than the competitors.
Neutral	Working this app is very good.....I appreciate .... But sometimes this app work slow.......But all of good

2 Related Studies

Many of our studies are motivated by earlier research in these fields, whereas others are merely intended for our own understanding. Chayawan Poromatikul et. al. [5] combine and contrast ideas and frameworks to meet a purpose, but the literature lacks a clear relationship that is special to mobile banking. Two native Thai speakers created a questionnaire in English that was afterwards translated into Thai as a source of data in 2019. It was decided that 399 of the 556 sent questionnaires were full and usable after 403 of them were returned. XLSTAT, PLS-SEM, and the ECSI model are the approaches used to produce the results. Henry Gao et. al. [6] used a dataset of restaurant reviews based on the comparison of NLP to show the difference flanked by both negative and positive sentiment. The statistics labels were stripped from 1,000 sets of data acquired through Kaggle. VEDER, Distil Bert, and an enhanced VADER were combined with LSTM to determine the accuracy of the model and evaluate its polarity for restaurant reviews TN, TP, and FP with Distil Bert showing the greatest accuracy at 92.4%. Jinghua Zhao et al. [7] established a method for analyzing user-generated content on social media and predicting individual qualities utilizing BN, SVM, RF, and attention-based LSTM algorithms. predicting social media users' personal traits using the LSTM model. When the data sets were created and randomly classified according to the 7:3 ratio, the most accurate models used LSTM algorithms with recall, attention, and F1-measure outcomes. Training materials is created for 10 periods, and the valuation set is evaluated for 10 weeks. From the perspective of Bangladesh, Md. Sabab Zulfiker et. al. [8] assess how users perceive the two most well-known online transportation providers, 'Pathao' and 'Uber'. Naive Bayes classifier exceeded Decision Tree and SVM with a precision of 87%. C. Chauhan et. al. [9] employed machine learning procedures to differentiate between positive and negative feedback. They looked over quite a few papers and established that Naive Bayes formed effective outcomes, but the results differed based on the situation, the approach, and the objectives. Tuhin et. al. [10] recognized and categorized emotions in various dimensions from all throughout Bangladesh, two distinct methodologies were presented. Using a data set of 7400 Bangladeshi phrases, 90% accuracy was achieved. Afterward, they compared their article against two others, which both had SVM scores of 93% and document frequency scores of 83%. Johannes Huebnerl et. al. [11] constructed a multidimensional scale that captures all factors that impact the quality of applications, for mobile health apps named Mobile App Rating Scale (MARS) was developed. MARS, uMARS, and FinMARS subscales methods are used which resulted in engagement, alpha=0.78, ICC=.67 (95% CI .58 to .75) Functionality, alpha=0.62, ICC=.66 (95% CI .59 to .72) Aesthetics, alpha=0.92, ICC=.73 (95% CI .63 to .81) Trust Signaling, alpha=0.82, ICC=.55 (95% CI .46 to .63) App Value, alpha=0.66, ICC=.50 (95% CI .35 to .62) Financial Behavior, alpha=0.68, ICC=.62 (95% CI .51 to .70) Nadhila Idzni Prabaningtyas et. al. [12] According to research, how well clients take to mobile banking relies on the extent of availability the system can provide. They gathered data from a variety of web platforms, including Go-Pay, OVO Reviews, Amazon, and others. The investigation was carried out using SGD and SVM techniques. According to the study's findings, 92% of upper-income nations, 77% of middle-income countries, and 57% of lower-income countries have accurate payment and trust labels. Dr.C. Kathiravan et. al. [13] The SERVQUAL model contains 10 measurements to capture customers' opinions. According to SERVQUAL, a survey on Bangladeshi mobile banking users reveals that the country's consumers have varying perceptions regarding the practice. According to the findings of a different research on sentiment analysis related to the use of mobile banking applications, Linear Regression scored 74.40%, Naive Bayes scored 66.01%, Decision Tree scored 94.37%, Random Forest scored 93.69%, and Support Vector Machine (SVM) scored 87.55%. Majesty Eksa Permana et. al. [14] Arithmetic and composed discourse of sentiments, emotions, and reviews with alternative names Opinion Mining are delineated as Sentiment Analysis. The methods LDA and Naive Bayes are used here. Naive Bayes' theorem shows the relationship between a conditional probability and its inverse to predict text sentiment. A total of 6194 dataset and attributes are being used with results LDA- 30%, NB-80%, Best accuracy LSTM 98% where Source of data is Google Play Store. Angdresey and Wong Kar's Sentiment analysis research has been done to gauge popular opinion of presidential candidates utilizing Twitter data and comparing the findings using Naive Bayes, KNN, and SVM. Misinem et. al. [15] The sentiment analysis of the use of mobile banking applications yielded the following results: LR (74.40%), NB (66.01%), DT (94.37%), RF (93.69%), and SVM (87.55%). The Decision Tree algorithm produced the greatest accuracy results, 94.37%, and Naive Bayes produced the poorest results, 66%. A. G. Asali et. al. [16] used data acquired from tweets to examine customer opinion on mobile banking. According to research on 5014 tweets, negative tweets account for 49.8% of all tweets, followed by only positive tweets at 5.7%, neutral tweets at 44.5%, and other tweets. Model building and evaluation, text mining, and text classification are effective techniques that have been applied throughout the process. Abdul Gaffar Khan et. al. [17] In Bangladesh, mobile banking first appeared in 2011, and 95% of users in 2013 used mobile devices, just 13% of users used mobile banking. The percentage of people using mobile banking will increase by 89% in 2021. Structured partial least squares modeling is used. The outcome of this study shows 0.0770 2.098 H1 Tangibility H2 Reliability 0.1815 3.741** Supported, H3 Responsiveness 0.3165 5.914**, H4 Assurance 0.1750 3.359** Supported, and H5 Empathy 0.2758 5.532** Supported. Johannes Huebner et. al. [18] include user reviews, valuable details about how users evaluate the app, which may be given to the app developer along with further ideas for enhancement. 34,1989 reviews were gathered. With an average rating of 2.773 from 94.0% of the applications and a Cohen's kappa of 0.933, perfect agreement was achieved using machine learning, web scraping, VADER, OLS regression, and ANOVA approaches.

3 Methodology

Four subparts make up this component. Dataset, data preparation, word clouds, and applying our algorithms are those same components. The entire work process for our planned effort is portrayed in Fig. 1.

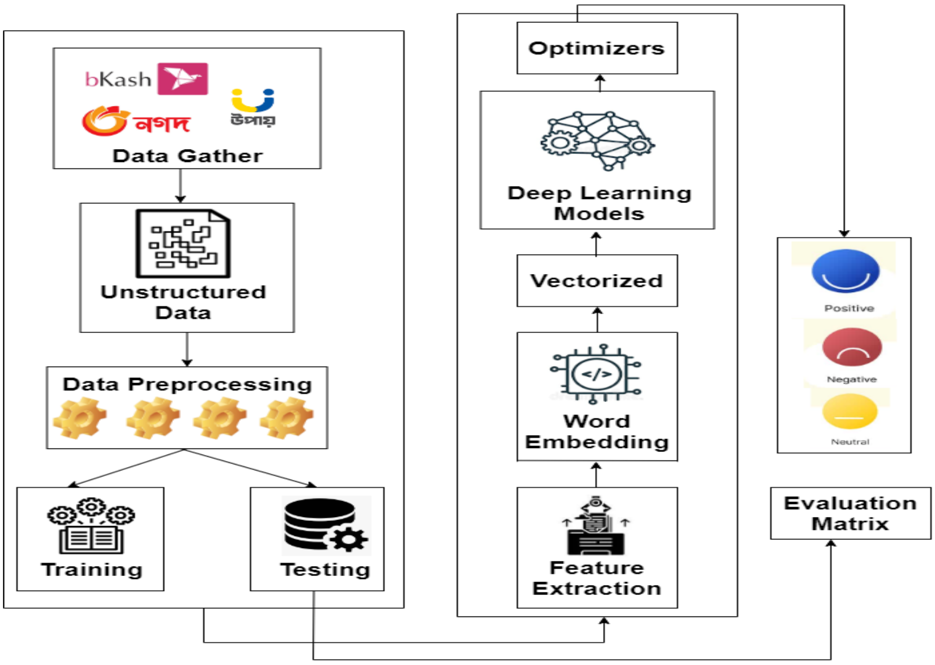


Fig. 1. Entire Work flow.

3.1 Data Collection

In our study, the reviews of a few renowned mobile fintech apps, including Bkash, Nagad, Upay, and Rocket, from the Google Play Store were compiled. These applications yielded almost 5414 data sets, which were classified into three distinct groups (Negative, Neutral, and Positive). There are 1730 data points that are positive, 1722 data points that are negative, and lastly, 1962 neutral data points. Although there are several online datasets, the one that was utilized is distinctive and contemporary, and it was made by ourselves.

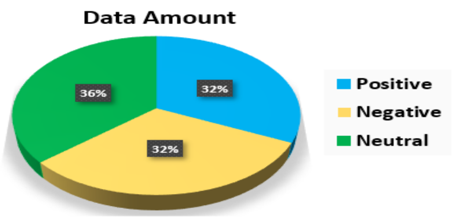


Fig. 2. Pie chart of total dataset.

3.2 Data Preprocessing

We understand that each and every dataset includes a variety of data types, including unorganized, lacking, unlabeled, totally inaccurate, etc. [19][20]. This collection was quite good when it was retrieved publicly. They produced this excellent dataset by adhering to specific guidelines. Here is a diagram that breaks out all these procedures. Based on the meaning of the sentences and the number of given star rating, we have classified them in our study as positive, negative, or neutral.

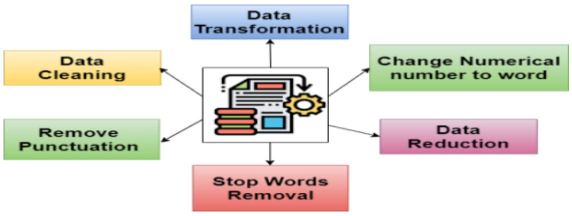


Fig. 3. Data preprocessing process of dataset.

3.3 Tokenization

Tokenization is the process of exchanging PANs, PHI, PII, and other sensitive information items with surrogate values, or tokens. It is a kind of encryption; however, the two concepts are sometimes used interchangeably [21].

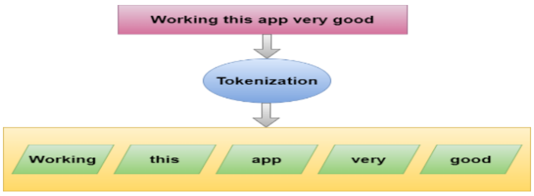


Fig. 4. Tokenization process.

3.4 Convolutional Neural Network (CNN)

CNN does not require human feature extraction because it learns directly from input, which is known as Deep learning network design. Convolution, pooling, and fully linked layers make up the three layers that make up CNN. They are highly skilled at seeing patterns in images that may be used to tell between objects, faces, and scenes. In addition, they are helpful for classifying non-image data, including time series, sound, and signal data. The dense layer is connected directly. The binary cross entropy loss function, the optimizing compiler "Adam," and a "SoftMax" activation in the thick layer have been used in our proposed system. We used 80% of all the datasets for training, and the rest of 20% was used for testing purposes.

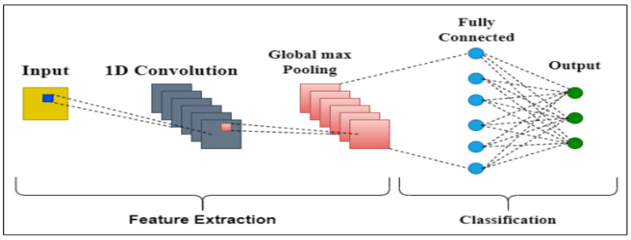


Fig. 5. CNN's model's architecture.

3.5 Long Short-Term Memory (LSTM)

Perpetual Neural Network, an LSTM subtype, seeks to address the long-term reliance problem of the RNN. By default, it has the capability to store information for long periods of time. The strand structure is similar to that of LSTMs, but the chain-like structure has a distinctive framework. In our approach, we introduced aspatial drop-out1D with a quantity of 0.2 after an embedded layer. It was 0.5 after putting the LSTM size in with the Dropout layer. "Adam" is the name of the effective measure that we employed.

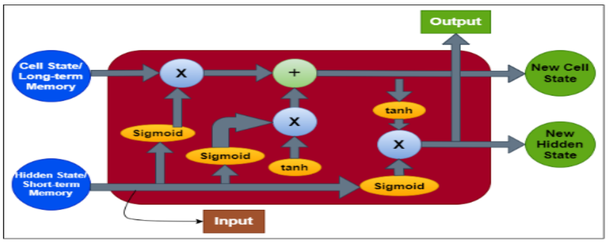


Fig. 6. LSTM model architecture.

3.6 Bidirectional Long Short-Term Memory (BiLSTM)

A model for sequence processing made up of two LSTMs is called a bidirectional LSTM, or a BiLSTM. One of which accepts input in the forward direction, while the other does so in the reverse direction. The network can access additional data with the use of BiLSTMs, which helps the context of the algorithm. In contrast to the LSTM network, the Bi-LSTM method comprises two concurrent steps that communicate in simultaneously forward and backward portions to maintain reliance in two situations. For this work, a statistical approach to BiLSTM with glove word embedding was used. Out of the total dataset, we used 80% of the resources for training and 20% for validation.

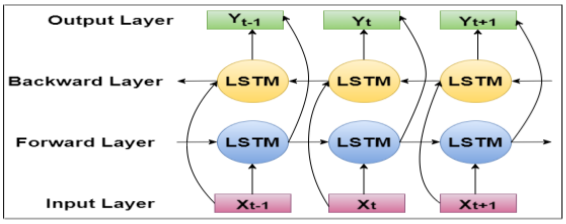


Fig. 7. BiLSTM model's architecture.

3.7 Parameter Tuning for Models

Table 2. Parameter tuning.

Models	Batch Size	Epochs	MaxLn
Glove & CNN	256	70	1000
Glove & LSTM	256	70	1000
Glove & BiLSTM	256	70	1000

4 Result Discussion and Analysis

Accuracy: The ability of a device to measure an exact figure is referred to as accuracy. It depends on whether the measured value approaches a standard for the actual value. To improve accuracy, more readings must be considered. The modest reading reduces the error of the computation. Here, the bidirectional LSTM has performed better than the conventional LSTM and CNN since the input flows in both directions (backward and forward architectures).

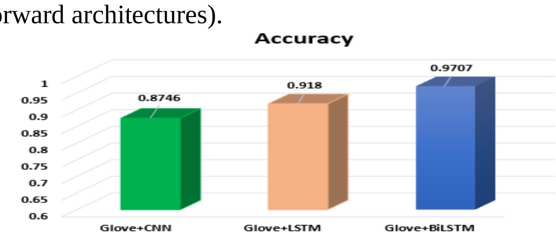
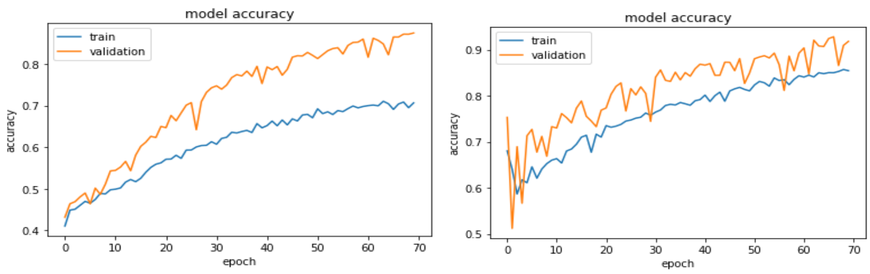
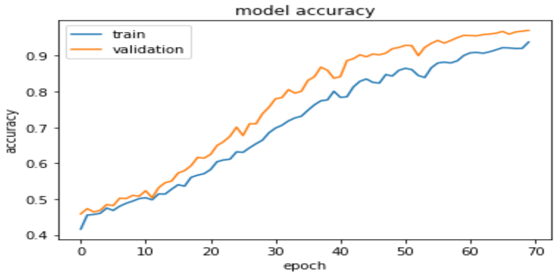


Fig. 8. Accuracy of all models.

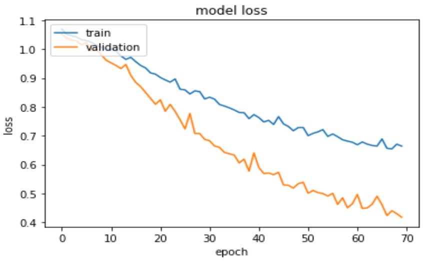


1.CNN 2. LSTM

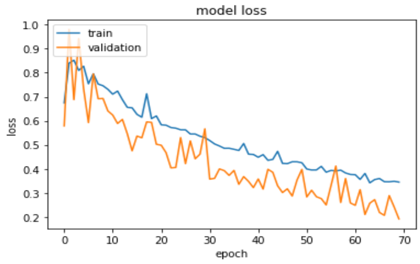


3.BiLSTM

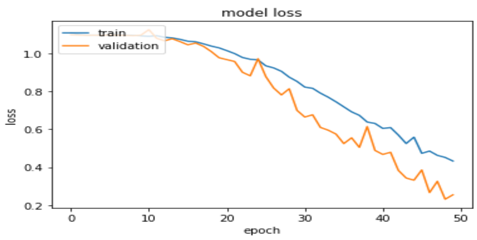
Fig. 9. Training and validation accuracy for all models.



1.CNN



2. LSTM



3. BiLSTM

Fig. 10. Loss graph of all models training and validation.

Word cloud: As of late, there has been an exponential growth in the volume of text data, necessitating a greater and greater demand for its analysis. Word clouds are an excellent method to analyze text data by displaying tags or words, with the frequency with which a word appears indicating its importance.

Fig. 11. Full dataset's Word Cloud.

Subjective sentences typically refer to specific people's viewpoints, emotions, and judgments, even when they are unbiased. Facts are related in statements. Yes, subjectivity floats. has a value ranging from 0 to 1. Polarity and a floating object value ranging from -1 to 1.

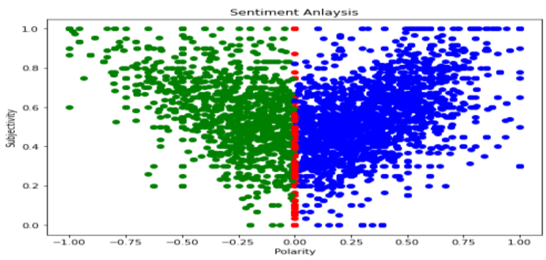


Fig. 12. Subjectivity and Polarity of dataset.

Precision: A classification model's capacity to focus only on related data items. To calculate accuracy, divide the total of genuine and false positives by the maximum actual positives.
Recall: Capacity of a model to identify each pertinent occurrence in a data source. Mathematically, recall is computed by isolating the quantity of true positives by aggregate of false negatives as well as real positives.
F1-score: F1-score evaluates a model's precision on a set of data. It is used to assess categorization systems that categorize events as either "positive" or "negative." Information retrieval systems like search engines and machine learning models, especially those utilized in natural language processing, are widely evaluated using the F1-score.

Table 3. Evaluation matrix of models.

Models	Classes	Precision	Recall	F1-Score
CNN+Glove	Positive	.81	.83	.82
	Negative	.98	.90	.93
	Neutral	.83	.90	.86
Glove+LSTM	Positive	.90	.89	.89
	Negative	.97	.93	.95
	Neutral	.88	.93	.90
	Positive	.94	.98	.96
	Negative	.99	.98	.98

Glove+BiLSTM	Neutral	.98	.95	.97

From the table, for all three classifiers, it is evident that BiLSTM outperformed CNN+Glove and LSTM+Glove (positive, negative, and neutral). Precision, F1-score, and recall for all the three classifiers were highest for BiLSTM (positive, negative, and neutral).

Table 4. Calculation of Macro and Weighted average.

Models	Macro/weighted average	Precision	Recall	F1 score
CNN+Glove	Macro average	.870	.870	.870
	Weighted average	.880	.870	.880
LSTM+Glove	Macro average	.920	.920	.920
	Weighted average	.920	.920	.920
BiLSTM+Glove	Macro average	.970	.970	.970
	Weighted average	.970	.970	.970

The overall positive forecast calculated as the ratio of positive numbers is what is meant by sensitivity. Sensitivity and specificity are complete opposites. demonstrates our model's sensitivity and specificity visually. This visual representation demonstrates that Glove+BiSTM results have higher sensitivity and specificity than other results.

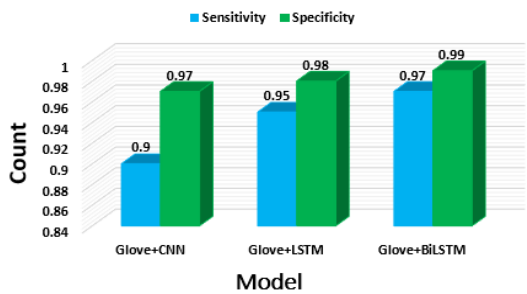
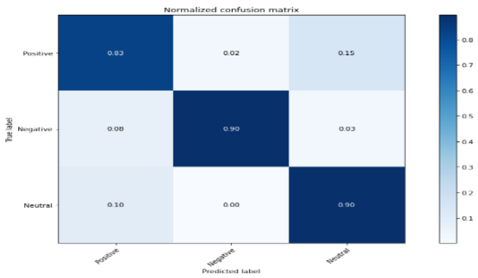
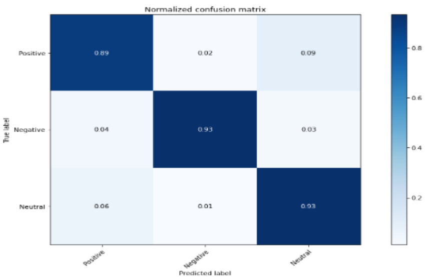


Fig. 13. Sensitivity and Specificity accuracy of models.

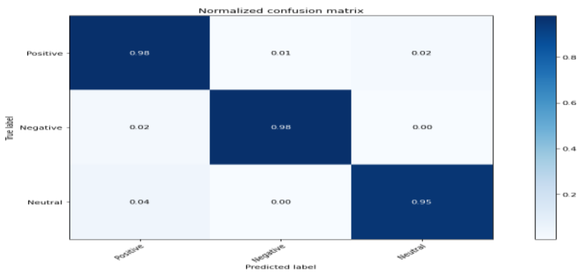
Confusion matrix: An approach for describing the effectiveness of a classification system is the confusion matrix. [22]. Classification accuracy alone might be misleading if the dataset contains more than two classes or if the number of observations varies significantly between classes. By creating a confusion matrix, it may be possible to gain a better grasp of the strengths and shortcomings of the classification model.



1.CNN



2.LSTM



3.BiLSTM

Fig. 14. Confusion Matrix of models.

By partitioning the entire number of false positives by the entire number of negatives, the FPR is determined, and the FPR for Glove+CNN is a bit higher. BiLSTM has the lowest FNR value. All three algorithms in our model showed higher NPV values, with BiLSTM marginally outperforming the other two. Glove+CNN has a higher FDR score, which is calculated by dividing the total number of discoveries by the total number of false discoveries. The efficiency of the algorithms was assessed using the three most commonly used accuracy measures for regression models: MSE, MAE and RMSE. The RMSE, MAE and MSE of Glove+CNN are marginally greater than those of the two additional models.

Table 5. Performance measure matrix of CNN, LSTM and BiLSTM.

Model	FPR	FNR	NPV	FDR	MAE	MSE	RMSE
Glove+CNN	.024	.094	.923	.023	.194	.075	.271
Glove+LSTM	.013	.044	.956	.017	.089	.036	.190

Glove+BiLSTM	.004	.022	.980	.005	.032	.013	.117

The fact that we achieved the output we anticipated for the input shows how effectively our model performed, as seen in the table.

Table 6. The Predicted testing results of three models.

Model	Sentences	Actual Class	Predicted Class
Glove+CNN	Good experience but one thing I would like to suggest add some new features like shortcut for scan to pay/cash out It will be easier and less time consuming then	Positive	Positive
	Poor app not available in skitto Mobile recharge and my account have a problem I dont send money Cash out or payment only able to mobile recharge	Negative	Negative
	A very good one and bonus is also available the bonus for opening an account is 25 rupees	Neutral	Neutral
Glove+LSTM	Good experience but one thing I would like to suggest add some new features like shortcut for scan to pay/cash out It will be easier and less time consuming then	Positive	Positive
	Poor app not available in skitto Mobile recharge and my account have a problem I dont send money Cash out or payment only able to mobile recharge	Negative	Negative
	A very good one and bonus is also available the bonus for opening an account is 25 rupees	Neutral	Neutral
Glove+BiLSTM	Good experience but one thing I would like to suggest add some new features like shortcut for scan to pay/cash out It will be easier and less time consuming then	Positive	Positive
	Poor app not available in skitto Mobile recharge and my account have a problem I dont send money Cash out or payment only able to mobile recharge	Negative	**Neutral**
	A very good one and bonus is also available the bonus for opening an account is 25 rupees	Neutral	Neutral

5 Conclusion and Future Work

Based on user evaluations posted on the Google Play Store, this survey aims to ascertain how users of mobile banking apps operate. like bKash, Nagad, Rocket, Upay, and Sure Cash feel about them. Total of 5414 amounts of data were collected by text mining from the reviews section of the Google Play Store, where people share their thoughts and experiences. Nowadays, it is quite usual to base an individual's decision on the feedback provided by actual consumers or users for a particular item or service. In order to use the well-formed data in our research, we transformed the unstructured data. After categorizing the data into three groups and using three widely used deep learning methods: LSTM, CNN, and BiLSTM with Glove on the review dataset. According to the study's findings, the Glove+BiLSTM algorithm and Glove+LSTM can both generate reliable models with accuracy values of 97.07% and 91.80%, respectively. and 87.46% for Glove+CNN. This research only gathers reviews written in English, and as most reviewers employ unconventional language, it might be challenging to determine a word's meaning. For our future work, we want to work with a large dataset, combining Bangla and English dialect reviews and adding more deep learning algorithms to do a comparison study.

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