The Corporeality of Infotainment on Fans Feedback Towards Sports Comment Employing Convolutional Long-Short Term Neural Network

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***Abstract*—In ODIs, World Cups and T-20 matches of various sports like Football, Cricket, Hockey, Basketball and Badminton, fans express their feelings and emotions towards the players by posting their status on social media like Facebook, Twitter etc. By collecting these opinions and feelings of the fans from different mediums, we have focused our research on a sentimental analysis of the sport with a total of 3759 comments related to Football (both national, international), Cricket, Hockey and Badminton. Since sports related opinions have been taken up in Bengali, global vector (glove) word embedding techniques are used for pre-processing which can retrieve word meanings and synthetic information. It also specializes in creating word vectors, including the structure of word embedding infrastructure, and provides a special advantage over statistics. Three models have been proposed in our study, one of which is a hybrid model of CNN-LSTM. In the proposed CNN-LSTM model, the CNN model is used to quote various features from word embedding that reflect short-term sentiment dependence while creating long-term sentimental relationships between LSTM words. In comparison to the hybrid model, two single models CNN and LSTM are proposed in five categories (i.e. Positive, Negative, Neutral, Happy, Sad). The sport's dataset integrates the CNN-LSTM hybrid model with the glove embedding layer, providing 97.45% accuracy. Lastly, the LSTM-CNN hybrid models perform comparatively better, realizing the feeling of the fans' comments.**

Keywords—Sports sentiment, Word embedding, Glove, Convolutional neural network, Long-short term memory, CNN-LSTM, Natural language processing.

I. Introduction

Last couple of years, Sentiment analysis (SA) has become a very demandable part of the research field. SA is a subfield of Natural Language Processing (NLP) that investigates and predicts human emotions. SA is classified into four categories: fine-grained analysis, feelings recognition analysis, aspect-based evaluation, and intent analyzer.. The analysis of emotion is an area that analyzes people's opinion [1], sentiment and emotion from various social sites, comments, reviews etc. It is important because it has a wide range of useful applications based on re-views or opinion mining [2]. Organizations all over the world are trying to embrace the ability to extract insights from social data. The primary goal that uses SA is to learn about the genuine feelings of the people who live in our community [3].

Classification technique refers to the process of determining whether such a type of prose is positive, negative, or neutral. NLP is a subset of ML that is used in textual analysis and is a component of a SA scheme [4]. Text-based sentiment analysis is simpler than others because machines can quickly determine it when we use textual data. Assume that "I am a researcher" and "I am not a researcher" are easily distinguished by their polarity [5]. However, other data such as audio-visual data, emojis, tone, and so on can make verbal communication harder to comprehend, and objects become really complicated when trying to analyze a large amount of data containing both subjective and objective responses [6].

Sports (Football, Cricket, Badminton, Hockey) in Bangladesh, are very popular right now. People are also commenting on every match. They express their deep feelings about our country's sports. Recently sports related comments are moving around us because our Bangladeshi players are not doing well in other countries for both football and cricket. They tried hard but could not succeed. In this situation, people of Bangladesh are commenting good or bad on different social me-dia. There are some people who love their country's sports very much but they cannot express their feelings about sports freely. That's the reason we can try to predict their emotions about sports. Using Bengali Sports comments because we classified Bengali sport data too easily and understand too shortly.

In our work, we used Bengali Sports comments text to classify their opinions. SA is significant as it has a wide range of useful applications based on reviews or opinion mining. They share their opinion as a comment. Both Bengali and English comments, they have shared. We collected Bengali Sports comments in different Facebook pages. In our own build dataset, it has five classes (Positive, Negative, Neutral, Happy and Sad). Some of the comments were structured but most of the comments were unstructured. In this paper we used a hybrid algorithm called Glove+CNN-LSTM. In this hybrid model, we used two known algorithms which are CNN and LSTM.

II. RELATED WORKS

Several of our work is inspired by past works in such areas, while others are for our own knowledge.

(Lutfun Nahar et al., 2019) presented the paper on filtering Bengali political, Sports and social media news to get more accurate news in a short way. 1000 Bengali comments used in ML techniques such as NB, SVM and neural networks to work in this research. For Sports news NB performed better than the two other methods [7]. (Rian Ardianto et al., 2020) E-Sports for education curriculum was demonstrated with the data of crawling the social media platform Twitter. ML classifiers NB and SVM used to predict E-Sports education. Naive Bayes Predict e-sports based sentiment better than the Support vector machine [8]. (Shamsul Arafin Mahtab et al., 2018) analyzed Bangladeshi Cricket news through some machine learning algorithms with Bengali Sports comments in various platforms like blogging, social media etc. Using SVM to predict real life opinion on Bangladeshi Sports comments with TF-IDF vectorizer. They also used the ABSA (Aspect Based Sentiment Analysis) dataset for comparison along with SVM, DT and MNB. After all, the SVM method performed better than other models [9]. (Clarissa Miranda-Pena et al., 2021) used ML approaches to predict the polarity of 3000 tweets to EPL season 19/20. The aim is to design a versatile system that automatically per-forms the way of collecting a corpus of tweets previous to a tournament and categorizing their emotion in order to determine the likelihood of a finals game by trying to analyses interconnection's crucial role [10]. (Abdullah Aziz Sharfuddin et al., 2018) Used social media Bengali comments to predict its accurate opinions with almost 15000 data fetched from Facebook. After data preprocessing, cleaning, some traditional classifying ML models SVM, DT Classifier, Logistic-Linear Regression used. Proposed models were mixing up with LSTM, RNN and BiLSTM. The Proposed model gave better accuracy than other classifiers [11]. (Md. Ferdous Wahid et al., 2019) prepared their dataset from various social media, blogging sites etc. Using word embedding for word vectorization and long interconnections, they used the LSTM model and its accuracy was 95% which is higher than the accuracy of any previous method [12]. (Asif Hasan et al., 2016) introduced a method for classification tasks of BRBT that used LSTM with Boolean and unambiguous cross-entropy wavelet coefficients. They used 9337 data for their proposed algorithm which mixed up with Bangla and Romanized data of 6698 and 2639. Highest accuracy comes from the Bang-la dataset [13]. (Kamal Sarkar et al., 2017) used multinomial NB and SVM to categorize Bengali feelings, which is classified as positive, negative, or neutral; a feature amount monitored RNN method has been used. They used a different combination of features like Unigram, Bigram, Trigram, and SentiWordnet. Their Bengali tweet set of data was publicly released for the 2015 SAIL competition. The preliminary results show that their own proposed technique outperforms the correct way in the SAIL 2015 sentiment analysis competition [14].

(Marina Bagić Babac et al., 2016) mainly focuses on who, how and why people created sports websites and express their opinion to others. This paper analysis based on Facebook posts and comments of top five football clubs in the 2015-2016 session. They collected data from social media for both men and women and expressed their soft emotions through creating sports websites [15]. (Adela Ljajić et al., 2015) presenting text comments analyzed in sentiment analysis for the area of Sports. Data collected from social media was 1194. They used different types of Sports data like football, basketball, tennis etc. TF-IDF method used in this article for vectorization and one machine learning algorithm was used for this work, which was logistic regression [16]. (T Vijayakumar et al., 2020) continue to present challenges, such as the increasing difficulty of hyper parameter selection. The cost of computing adjoint and forward operators [17]. (JIZ Chen et al., 2021) proposed a deep learning-based financial fraud detection technique. When a huge amount of data is involved, paper is used [18].

III. DATASET PREPARATION

The dataset preparation phase has two main parts, i.e. (i) Data Collection and (ii) Data Preprocessing.

A. *Data Collection*

We have collected our dataset from different social media pages or groups. There are many people who share their opinion or feelings about different types of sports like Football, Cricket, Badminton etc. We gathered Bengali comments that express people's opinion easily. We collected around 3759 data from different sources And it was our own build in dataset. This dataset has 5 different classes, Positive, Negative, Neutral, Happy and Sad. The Dataset has three columns, First is Comments, then Tag and the last one is Category. We tagged these Bengali comments by football, cricket, badminton and hockey. Below we show the amounts of all categories.

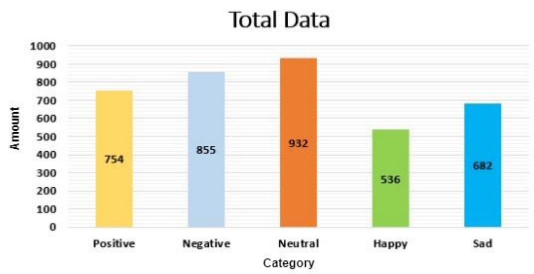


Fig. 1. Amount of all the categories of our dataset.

B. *Data Preprocessing*

Data preprocessing is the method of changing raw information into well sets of data so that data mining analytics can work properly. Data preprocessing is a necessary phase because when we collect data, some errors remain, and there is a defined way to resolve such issues. The suitability or inadequacy of data preparation is directly related to the success of a data analysis project. Data is preprocessed in a series of processes. Stop word removal is among the most popular pre - processing stage in various NLP tasks. The concept would be to completely eliminate words that appear frequently in all of the appears in a document.

Fig. 2. Preprocessing dilution processs.

IV. METHODOLOGY

Every work is done sequentially and there is a work procedure to complete full work. In this paper, we use two deep learning models and one hybrid model. This work we use Glove word embedding. Below this figure represents our whole work process.

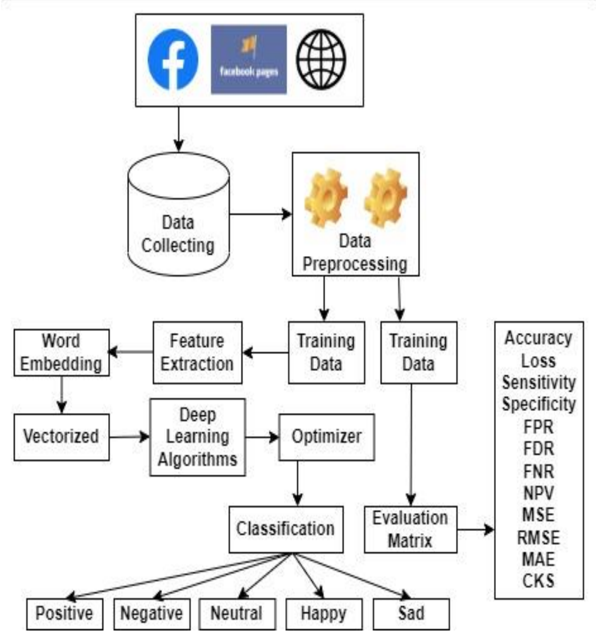


Fig. 3. Overall work procedure.

A. *Word Embedding and Optimizer*

The mathematical representation of words or documents is known as word embedding. Essentially, we can use this to transfer words into numbers [19]. Word embedding is used when we need numbers to train a machine learning technique. In this paper, we used Glove word embedding for different algorithms.

Glove: Glove is a word vector demonstration generated by an unsupervised learning algorithm. Glove is yet another word embedding execution that makes use of a co-occurrence matrix. This model takes into account global properties in a dataset.

Adam optimizer: Adam optimizer is essentially a hybrid of AdarGrade and RMSProp. RMSProp uses the square derivative, whereas Adargrader uses the first-order derivative or the normal derivative (gt) (gt^2).

B. *CNN Model*

Though we all realize, a convolutional neural network is a non-linear perceptron applicable to the results of a specifically designed to support, followed by a full way of communication for categorization after the pooling operation. In past years, CNN demonstrated innovative consequences in some NLP tasks, one of which is the categorization of sentences, such as the categorization of simple phrases into a set of predefined classifications. The filter, also renowned as the kernel function, is at the heart of convolutional operations. It accomplishes extraction of features by sliding through the original matrix from top to bottom and left to right. The depth of the kernel function in NLP is usually equal to the size of the original matrix, and the kernel function only slides in the top and bottom instructions, preserving the accuracy of the word as the fewest level of detail in the language.

C. *LSTM Model*

The LSTM network is a kind of RNN that can teach long-term dependence. To reach this aim, the center of LSTM is cell state, which can append or remove data from cells and selectively allow data to flow through the gate framework. The LSTM is formed by three gates: a forget gate, an input gate, and an output gate [20]. The forget gate gets to decide which data should be removed from the cell state, and the input gate defines which data should be added to the cell state. The cell state could be changed after these two functions have been determined. Finally, the output gate determines the optimum result of the system.

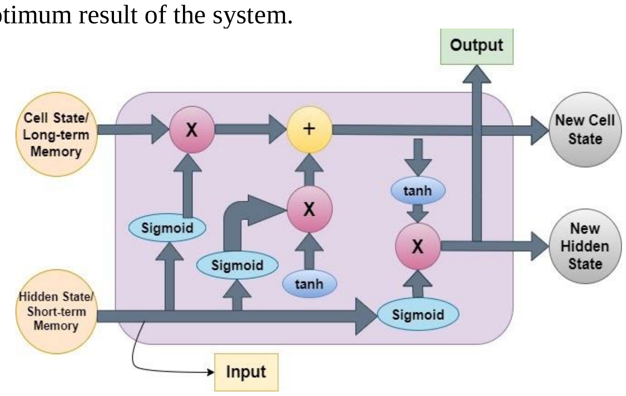


Fig. 4. Architecture of a typical LSTM model.

D. *CNN-LSTM Model*

CNN-LSTM is combined with two familiar DL models, which are CNN and LSTM. We use Glove word embedding in this model. All the layers add sequentially. Firstly, starting with the embedding layer and adding SpatialDropout1D, which value is 0.2. Then adding with convolution 1D layer which filters is 32 , kernel size is 3 and the activation function is relu. After adding those layers, we connected the Maxpooling1D layer whose pool size is 2 and dropout value is 0.5. After adding the conv1D layer then we added the LSTM layer. The dropout value of the LSTM layer is 0.5 and the activation function is softmax for dense layers. In this hybrid model we used Adam optimizer. The error function of this proposed model is "categorical crossentropy,"

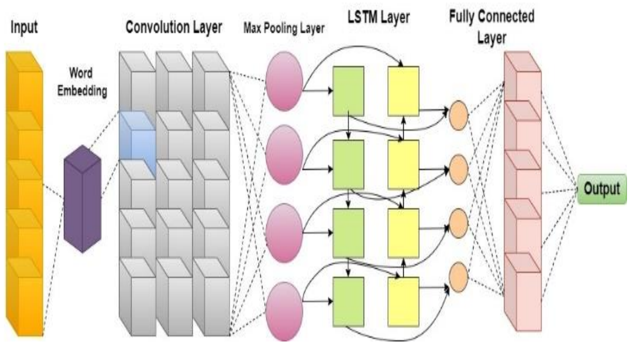


Fig. 5. Architecture of CNN-LSTM model.

E. *Algorithms Parameter Configuration*

This figure illustrates which parameters in our method we can use to get the best results.

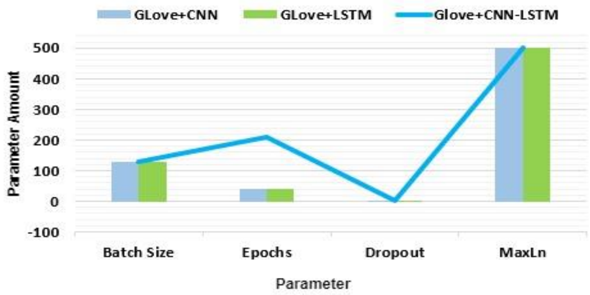


Fig. 6. Parameter tuning for models.

V. RESULT ANALYSIS & DISCUSSION

This figure shows the outcome of all the models. We have used two known models, CNN and LSTM. Their accuracy was 95.74% and 97.39%. We also combined a proposed model, CNN-LSTM which accuracy was 97.45%. CNN and LSTM algorithms outperforms shows with low accuracy than hybrid model. In this figure, we can see that Glove+CNN-LSTM model accuracy was much higher than others.

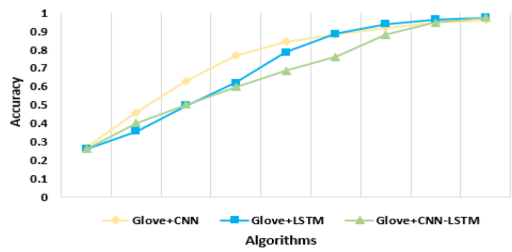


Fig. 7. Validation Accuracy of our models.

This figure shows that, training accuracy, loss and testing accuracy, loss of our three models.

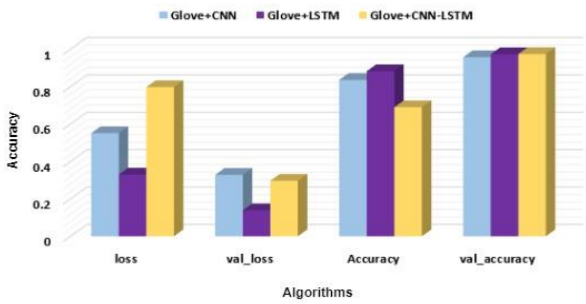
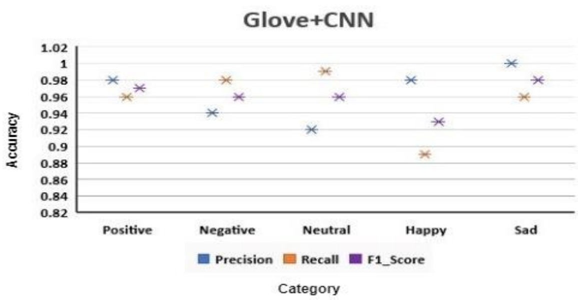
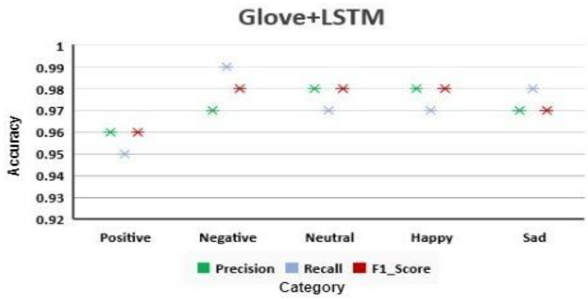


Fig. 8. Loss, val_loss, accuracy and val accuracy of our models.

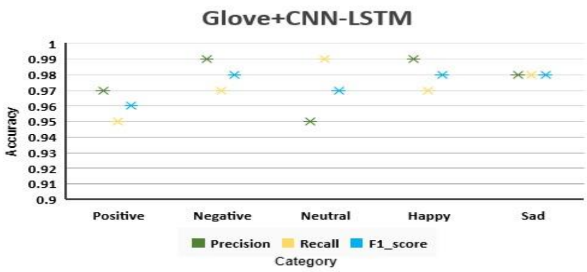
Below we figure out the three models precision, recall and f1_score. We categorized our data into five classes and we show precision, recall and f1_score of each class.



(a) CNN



(b) LSTM



(c) CNN-LSTM

Fig. 9. Evaluation Matrix for (a) CNN, (b) LSTM and (c) CNN-LSTM

The final average is called the macro average because all classes make a contribution to it. For Weighted average, the overall result of each category is weighted by utilizing its own length. For micro average all measurements make contributions to the last average total measure. The Micro, Macro and Weighted Average of the confusion matrix for our three separated modes are shown below.

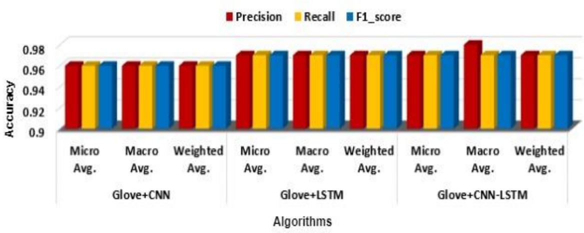
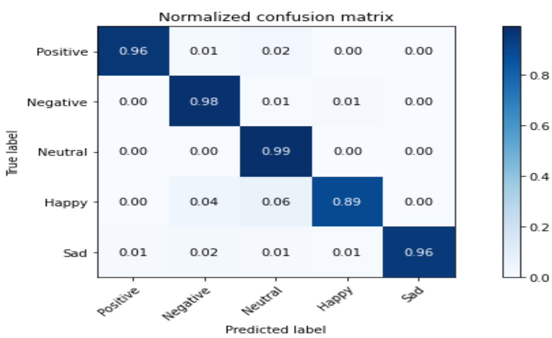
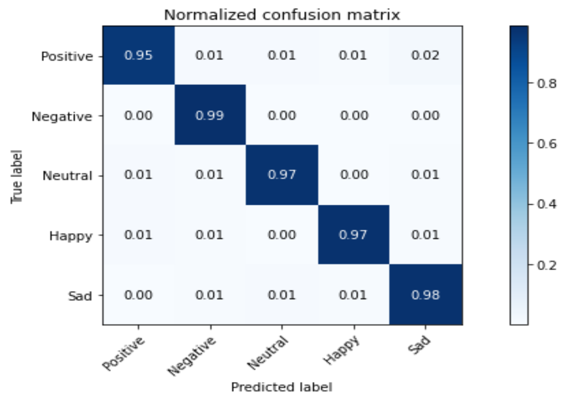


Fig. 10. Micro, macro and weighted average of three models.

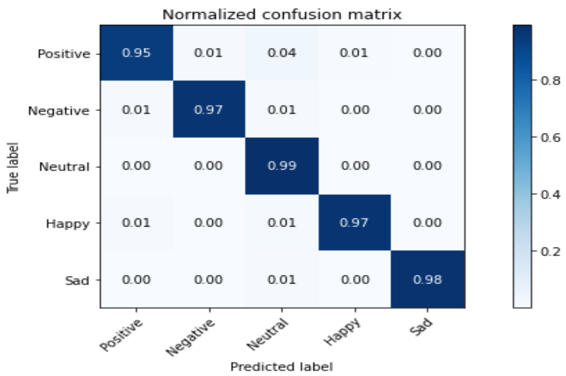
There are two main things in a confusion matrix: true value and expected values. The confusion matrix can tell us whether or not our classification algorithm is correct and if it is trying to make any mistakes. In our three models, the confusion matrix is a 5×5 dimensional matrix.



(a) CNN



(b) LSTM



(c) CNN-LSTM

Fig. 11. (a) Matrix of CNN model, (b) Matrix of LSTM model and (c) matrix of CNN-LSTM model.

We determine the ratio of true positive (TP) values and predicted positive values, called sensitivity. Specificity is the same as sensitivity but we calculate the negative values. Below this figure represent our three models sensitivity and specificity.

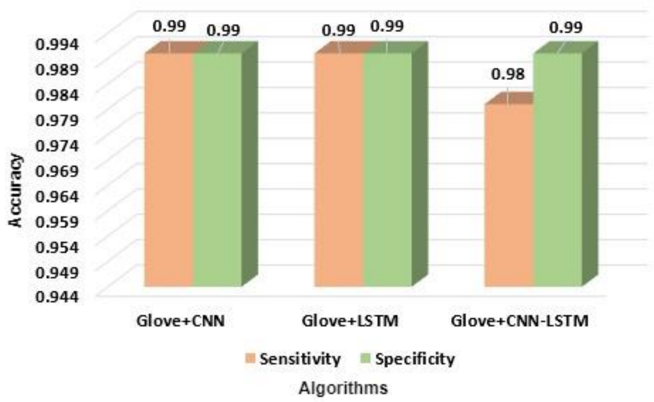


Fig. 12. Sensitivity ans Specificty accuracy of our models.

The false positive rate (FPR) is calculated as the quantity of incorrect positive predictions divided by the total number of negatives. FNR expressed as false neg-ative is an actual result in which the fully realize the negative class inconsistently. NPV means the percentage of subjects who were surely identified as negative compared to the total number of people who had negative test results. The overall number of discoveries is divided into the number of false discoveries, called FDR. Mean Absolute Error (MAE) calculated by averaging the actual difference among both expected and observed failures. The mean squared error (MSE) is the square differential between the true and predicted outcomes. RMSE refers to the stand-ard deviation of predictive performance.

TABLE I. THE CHARACTERIZATION OF THE RECEIVER AND THE EVALUATION MATRIX FOR CNN, LSTM AND CNN-LSTM MODELS.

Models	FPR	FNR	NPV	FDR	MAE	MSE	RMSE
Glove+ CNN	0.008	0.003	0.997	0.013	0.101	0.027	0.164
Glove+ LSTM	0.007	0.007	0.995	0.011	0.040	0.011	0.107
Glove+ CNN-LSTM	0.005	0.015	0.990	0.009	0.089	0.023	0.153

TABLE II. THE MODELS' PREDICTED EVALUATION OUTCOME.

Models	Sentences	Actual Tag	Predict Tag	Actual Category	Predict Category
Glove+ CNN	মনে হচ্ছে ফুটবল ম্যাচ গুলো টেলিভিশনে দেখা যাবে	Football	Football	Positive	Positive
	শ্রীলংকা এন্ড ইংলান্ড এই দুই দেশের খেলা দেখে কোন মজা নাই	Cricket	Cricket	**Neutral**	**Negative**
Glove+ LSTM	মনে হচ্ছে ফুটবল ম্যাচ গুলো টেলিভিশনে দেখা যাবে	Football	Football	Positive	Positive
	বাংলাদেশ ব্যাডমিন্টন থেকে একটা ছায়া সরে গেল মনে হচ্ছে	Badminton	Badminton	Positive	Positive
Glove+ CNN-LSTM	ক্লাব গুলো হয়তো শুধু মাত্র দেশি প্লেয়ার দিয়ে খোব একটা ফাইট দিতে পারবে না	Football	Football	Happy	Happy
	হকি খেলোয়াড়দের পরিবারে খোঁজ কি আপনারা নিয়েছেন	Hockey	Hockey	Sad	Sad

VI. CONCLUSION AND FUTURE WORKS

In this paper, we use sentiment analysis systems for different types of sports news Bengali comments opinion mining through different models. We predicted different types of sport category and their tags. We used four tags and five classes. Because of the fast expansion of social networks and internet news portals, sorting has become an absolute necessity in order to find the most actual news in the shortest period of time [21]. In this paper, we used two familiar DL models and one proposed algo-rithm which was combined by the first two DL models. We used CNN and LSTM with Glove word embedding, these two models' accuracy was 95.74% and 97.39% and hybrid model gained 97.45 %. We compare these three outperforms, Hybrid model accuracy is better than others. In Bangla language, very few papers were available in this term. Every work has some limitations and future works. Our papers limitation is short data

In the future, we will collect more data because if we create a strong dataset for huge data then our algorithms predict the actual theme. Further We will use dif-ferent types of supervised algorithms like RNN, ANN etc. In this paper, we used five classes. Furthermore, we will use more than five classes. In future We will add more pre-processing steps.

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