Incremental Learning based Optimized Sentiment Classification using Hybrid Two-Stage LSTM-SVM Classifier

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***Abstract*—Sentiment analysis is a subtopic of Natural Language Processing (NLP) techniques that involves extracting emotions from unprocessed text. This is commonly used on customer review posts to automatically determine if user / customer sentiments are negative or positive. But quality of these analysis is completely dependent on its quantity of raw data. The conventional classifier-based sentiment prediction is not capable to handle these large datasets. Hence, for an efficient and effective sentiment prediction, deep learning approach is used. The proposed system consists of three main phases, such as 1) Data collection and pre-processing, 2) Count vectorizer and dimensionality reduction is used for feature extraction, 3) Hybrid classifier LSTM-SVM using incremental learning. Initially the input raw data is gathered from the e-commerce sites for product reviews and collected raw is given to pre-processing, which do tokenization, stop word removal, lemmatization for each review text. After pre-processing, features like keywords, length, and word count are extracted and given to feature extraction stage. Then a hybrid classifier using two-stage LSTM and SVM is developed for training the sentimental classes by passing new features and classes for incremental learning. The proposed system is developed using python and it is compared with the state-of-the-art classification techniques. The performance of the proposed system is compared based on performance metrics such as accuracy, precision, recall, sensitivity, specificity etc. The proposed model performed an accuracy of 92% which is better compared to the state-of-the-art existing techniques.**

Keywords*—*Sentiment analysis; natural language processing; incremental learning; long short-term memory; support vector machine; hybrid; dimensionality reduction; principal component analysis

I. Introduction

Sentiments play an important role in rational decision making, perception, memory, creativity, human intelligence, social interaction, learning and more. Sentiment analysis and Opinion mining is a subtopic of text mining and NLP (Natural Language Processing) that deals with the extraction of knowledge and automated discovery about people's opinions, evaluation and sentiments from textual data such as review websites, customer feedback forms and personal blogs [1,2]. Sentiment analysis and opinion mining is a region, which has received significant interest in recent times because of its application and practical usage in today's environment. Emotion analysis of text involves cautious modelling of context, association of words with different emotions and contexts with changing levels of magnitude making the identification of words for document representation. Emotions are categorized into surprise, sadness, anger, fear, excitement and disgust [3]. For example, a sentence containing beautiful morning #amazing, the word amazing could be related strongly with emotion joy, morning could be weakly associated with emotion joy and beautiful will be related moderately to emotions such as joy and love. Emotion lexicons capture such word-emotion associations [4]. To organize the data and improve classification performance, lexicon dependent holoentropy is applied. It is created to reduce the computational risk associated with solving a multidimensional problem. The similarity score between the keywords of all sentiment classes and semantic words is determined using combined holoentropy [5]. However, these methods rely on lexical resources (external) which are concerned with mapping words to a numerical sentiment score or categorical (positive, negative, and neutral). Clearly, the efficiency of the entire method intensely depends on one of the best lexical resources, which relies on it [6]. As a significance, the efficiency of certain widespread is available on lexical resources, which is in the task for classification of microblog posts.

Sentiment analysis (SA) using supervised machine learning algorithms is popular and provides better results compared to unsupervised machine learning algorithms. However, supervised approaches require a labelled training set, which is time and labor-intensive operation [7, 8]. Whereas, the unsupervised approaches don't need labelled training set. The emotions can also be acquired by the reviews, which can be collected not only from applications but also provide comment features such as Google Play Store [9]. Platforms like Amazon, Flipkart are regularly used by users/customers to give their sentiments about numerous subjects, including the product quality [10, 11]. Nevertheless, social media does not have rating system and companies being observed cannot instantly detect the sentiment of these remarks. As a result, many businesses and companies have a strong claim for sentiment classification. By using a machine learning method, computer can learn emotion form text. In machine learning, computers cannot solve problems by applying pre-programmed rules, but rather by creating a model that can evaluate an example [12]. Hence, it can anticipate a sentiment or emotion. Machine learning is also a part of AI (Artificial Intelligence), which is a subset of deep learning.

Deep neural networks are utilized by deep learning to obtain input data that can be used for improved representation and to complete a task precisely [13, 14]. Likewise, sentiment analysis using deep learning techniques has a better accuracy compared to the traditional machine learning techniques such as SVM and Naïve Bayes (NB). Multiple or hybrid classifiers are mainly used for better training and better performance metrics than the single classifier. The error of single classifier will be greater than hybrid classifier because in hybrid, the trained data of one classifier will be given to the input of another. so, the trained net will be effective compared to the single classifier. Incremental learning technique is necessary to develop the learning models or trained net, which is capable of adding newly available classes without the need of retraining the models. Though many techniques had performed better but the error rate and performance of the existing technique is not achieved well [15]. So, in the proposed research effective feature selection is designed to enhance the classification performance.

The contribution of the paper is as below:

- To acquire extraction of data from the raw data, pre-processing technique is used that consists of sentence splitting, tokenization, spell correction, stop-word removal and lemmatization.
- To extract datasets more conveniently and effectively, the count vectorizer and dimensionality deduction is used.
- To attain an effective classification, the hybrid two-stage LSTM-SVM approach is used.

The upcoming portion of the paper is organized as follows; Section II illustrates certain research articles related to existing methods used for sentiment analyzing. Section III describes briefly about the proposed methodology. Section IV explains the results and performance metrics of the proposed framework. Section V concludes the entire research work.

II. Related Work

Several feature selection algorithms have been introduced for choosing the most relevant features that are required for better classification. The most commonly used feature selection techniques are SVM and LSTM. Some of the existing feature selection technique used in sentiment analysing is reviewed below.

Fu X et al. [17] has performed sentiment analysis using long short-term memory networks (LSTMs). This method is based on combination of LSTM with embedded words for representation of text. However, embedded words carry more semantic data than the sentiment data, so that the embedded word will cause inaccuracy to the sentiment analysis. To solve these issues, a lexicon-improved LSTM model is developed, which uses the sentiment-based lexicon as an additional data for sentiment classifier to pre-train a word and then include embedded sentiment words that are not inside the lexicon. The usage of a hybrid sentiment embedding and word embedding can improve word representation accuracy. Furthermore, without the intention of improving the LSTM's ability to gather global sentiment data, a new method for identifying the sensitivity vector in common sentiment analysis is developed. The outcomes of this model have comparative or better results than the existing models. Londhe A et al. [18] proposed incremental approach using LSTM-RNN for aspect level sentiment analysis. Major outcome of the paper was automated aspect extractions with comparable accuracy.

Long F et al. [19] aim to investigate the sentiment interpretation of social media in Chinese text by incorporating the Multi-head Attention (MHAT) mechanism with Bidirectional Long-Short Term Memory (BiLSTM) networks, in order to overcome the lack of Sentiment Analysis, which is currently carried out using old machine learning techniques. BiLSTM networks retain the text's actual context and resolve the issue of long-term dependency. By performing numerous dispersed calculations, the MHAT process can obtain related data from a distinct illustration subspace, and impact weights are added to the generated text sequence. The numerical experiments reveal that the suggested model outperforms existing well-established approaches. Rhanoui M et al, [25] also investigate CNN-BiLSTM model for document level sentiment analysis.

Khanvilkar, G et al. [20] has designed sentiment analysis for product recommendation using random forest algorithm. Sentiment analysis is a tool for analysing natural language and determining human emotions. The purpose of emotion analysis is to identify the polarity of a person's textual opinion and it can also be used to provide product suggestions. Products can be recommended to another user based on user reviews. Sentiment analysis is used by major product websites to analyse the difficulties and popularity of the product. Sentiment analysis is usually described as a task with two classification classes: negative and positive. Using ordinal classification, this approach calculates the polarity of user-provided reviews. Using machine learning methods SVM and Random Forest, the system will determine polarity. Users will be given recommendations based on the polarity that has been attained.

Can, E. F et al. [21] has designed Multilingual Sentiment Analysis using RNN-Based Framework for Limited Data. Sentiment analysis is a type of NLP work that evaluates a user's feelings, opinions, and ratings of a product. The fact that sentiment analysis is primarily reliant on language is one of the most difficult parts of it. Language-specific word embedding's, sentiment lexicons, and even annotated data exist. Optimizing models for each language is very time consuming and labour intensive, especially for RNN (Recurrent Neural Network) models. From a resource aspect, gathering data for several languages is relatively difficult. A sentiment analysis approach based on RNN is trained with reviews in English and translated into other languages to do this. As a result, the model may be used to assess feelings in different languages. According to the experimental results, the robust technique of a single model trained on English reviews statistically achieves the benchmarks in other languages.

Anitha Elavarasi S. et al., [22] In the age of big data and internet technology, organisations can use sentimental analysis or opinion mining to collect feedback on their services or goods in a more accurate and effective manner. In this paper linear regression and support vector machine are applied to the IMDB data sets. There are 50000 movie reviews in the dataset, with both negative and positive polarity remarks. SVM classifier and logistic regression were used as machine learning algorithms. The outcomes were analysed through accuracy, precision and recall. In comparison to SVM, which has an accuracy of 81%, logistic regression has a higher accuracy of 90 percent, making it more successful than SVM.

From the above-mentioned literature studied, various feature selection methods are designed based on LSTM [17, 18, 26], BiLSTM [19, 25], RF [20], RNN [21, 27], SVM [22] and hybrid LSTM-SVM [23] techniques. But rate of error is high and accurate prediction is lesser while using this existing method. At the same time optimal feature selection subset is not attained in the existing algorithm. Therefore, selection of hybrid feature algorithm is designed in this proposed research for effective selection of features from the dataset.

III. Proposed Methodology

Natural Language Processing (NLP) technique is a Sentiment analysing process that contain extracting of sentiments associated with some raw texts.

Generally, on social media, people used to post customer reviews in order to automatically understand, whether it is positive or negative review but quality of these analysis is completely dependent on its quantity of raw data. So recently, researchers are trying to utilize large dataset for modelling the sentiment prediction. The conventional classifier-based sentiment prediction is not capable to handle these large datasets. So, for an effective and efficient sentiment prediction, hybrid models on hybrid platforms need to be used [16]. In this paper an efficient deep learning-based hybrid model for sentiment prediction is proposed.

Fig. 1 illustrates the architecture of proposed model. It consists of three phases: 1) Data collection and pre-processing, 2) dimensionality reduction and feature extraction, 3) classification and incremental learning are the three primary steps of the proposed system. The raw data for the input is initially obtained from the online platforms for product reviews such as Amazon, Flipkart and Snapdeal. The data is pre-processed to eliminate superfluous information as keywords, length, and word count are extracted after pre-processing. After pre-processing techniques, emotional features are extracted with count vectorizer and dimensionality reduction, which is used for extracting the unwanted words for reliable sentiment analysis and converting it to vector format. Then, for sentimental class prediction, hybrid two-stage LSTM-SVM approach is used for training the sentimental classes. The new classes and features are introduced during training phase for incremental learning.

A. Data Collection and Pre-processing

By reviewing the literature, it is found that aspect extraction and sentiment classification have not been studied satisfactorily on Yelp dataset [29]. This dataset is well described in results section. Pre-processing phase involves filtering noisy text using a variety of pre-processing techniques [24], such as sentence splitting, tokenization, spelling correction, lemmatization, case-conversion, stop-word removal and anaphoric reference resolution. These steps are used to omit irrelevant phrases to offer better categorization.

- Splitting: The technique of breaking up a text string in a systematic way so that the individual parts of the text may be processed is known as string splitting. For example, a timestamp can be divided into hours, minutes, and seconds. So that those values can be used in the numeric analysis.
- Tokenization: Tokenization is an action of dividing a sequence of strings into pieces such as symbols, phrases, keywords, words, and other elements called tokens. Tokens can be individual phrases, words or even whole sentences.
- Stop word removal: Stop words are a group of terms that are regularly employed in any language. In English, "and", "is" and "the" would easily qualify as stop words. Stop words removal phase is used in NLP and text mining applications to remove unnecessary terms, enabling applications to concentrate on the subsequent words accordingly.
- Lemmatization: Lemmatization describes the process of gathering words with the same lemma or root, but different meaning derivatives so that they can be analysed as a single item.
- Spell correction: Spelling correction is a well-known task in NLP. It uses techniques of "noisy and correct word mappings" data from numerous sources for automated spell correction.

B. Pre-processed Data Extraction for New Features

The new features are updated with the pre-processed data by using the below mentioned feature extraction process.

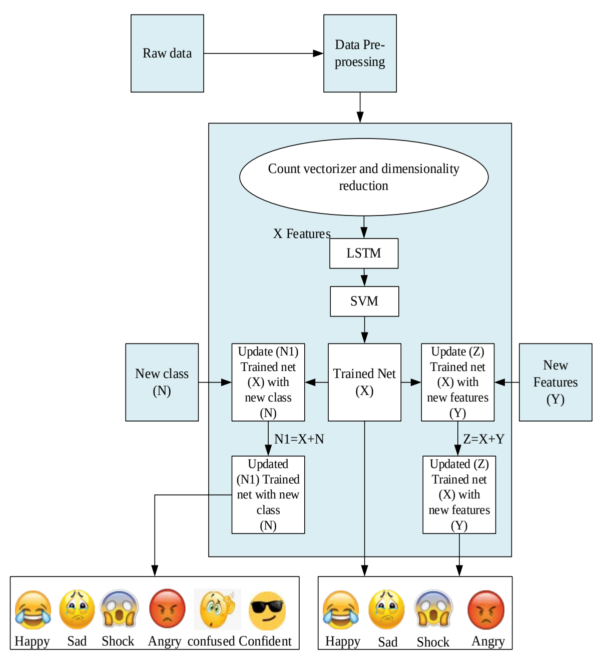

Fig. 1. Proposed Model of Sentimental Analysis and Text Classification.

- Words and Their Frequencies: The frequency counts of unigrams, bigrams, and n-gram models are considered as features. Additional research has been done to properly characterize this feature using the word presence rather than frequencies.
- Parts of Speech Tags: Adjectives, adverbs, and certain groups of verbs and nouns are excellent indicators of subjectivity and sentiment.
- Opinion Words and Phrases: Apart from individual words, phrases and idioms that can convey emotion as features. For example. Someone's arm and a leg,
- Position of Terms: The placement of a term in a text can have an impact on how much the term affects the overall theme of the text.
- Negation: Negation is a significant feature that can be difficult to interpret. When a negation is present, the polarity of opinion is usually altered.
- Syntax: Many academics employ syntactic patterns such collocations are used as features to learn subjective patterns.

If the pre-processed data is "best coffee" then the feature extraction of parts of speech will be 1, 1. This is because "best" is an adjective and "coffee" is a noun, both the parts of speech contain one word. So, the outcome of these pre-processed data is 1, 1. Likewise the other method such as opinion words and phrases, position of terms, negation and syntax are used for extracting the features. These extracted and the features are updated to the class.

C. Feature Extraction

Feature extraction is a process of extracting the required features for sentimental classes. The features are retrieved using a countvectorizer and dimensionality reduction, which reduces a large amount of raw data into smaller groups for analysis. A disadvantage of huge data sets is that processing a higher number of variables which demands a lot of computational resources. So that, the dimensionality reduction technique is utilised to solve this issue.

1) Countvectorizer: Countvectorizer is a major tool used in the python for converting the given text into vector with the frequency of each word that occurs in the entire text. This is helpful in converting multiple texts into each vector [24]. Each text sample and unique word is represented in row matrix and column matrix. Though the sentences of data may be in different size, the conversion of word to vector will be of same rows and columns for each and every other sentence.

2) Dimensionality reduction: It is necessary to smooth the input text dataset before applying a feature extraction and reduction model using Principal Component Analysis (PCA). PCA's primary goal is to extract important features from a big dataset and produce a lower-dimensional feature space. It may be used to extract data from a large number of different datasets. In addition, if we use a bigger dataset for analysis, the classifier will take longer to run. For this reason, feature extraction and dimension reduction are used to reduce the size and complexity of the data representation.

3) Hybrid two-stage LSTM-SVM classifier: In this proposed model, the hybrid two-stage LSTM-SVM approach is used for sentiment classification. Extracted features from dimensionality reduction are given as an input to this hybrid model.

a) SVM Classification: SVM is a state-of-the-art supervised ML algorithm which can be used for both regression and classification tasks. The SVM finds hyperplanes that differentiate the classes to perform classification task. For a set of training vectors belonging to separate classes, shown in (1):

$$\{(x^1, y^2), \ldots, (x^m, y^m)\}, \qquad x \in R^n, y \in \{1, -1\} \tag{1}$$

Mathematically a hyperplane for separating two classes can be represented as shown in (2):

$$\sum_{i=1}^{M} X_{ij}^{l} y_i^{l} + Bias^{l} \tag{2}$$

This can be written more in vector format as $< \mathrm{W}, \mathrm{X} > +\mathrm{b} = 0$. Here X is "an input vector or document", W is known as "a weight vector and corresponds to the normal vector" for separating hyperplane 'H', m represents "the number of input variables, in the case of text, this can be viewed as the number of words (or phrases, etc.) that are used to describe a document" and b denotes "the perpendicular distance from the hyperplane to the origin".

$$min\left|(w, x^i) + b\right| = 1 \tag{3}$$

From the above equation, it be evaluated that the optimal separating hyperplane given by:

$$w^* = \sum_{i=1}^{l} \alpha_i y_i x_i \tag{4}$$

$$b^* = -0.5(w^*, x_r + x_s) \tag{5}$$

α_i is the multiplier, x_s and x_r are support vectors that satisfies each class $\alpha_r > 0, y_r = -1;\ \alpha_s > 0, y_s = 1$.

b) LSTM Classification: LSTM is a variant of RNN, it deals with the vanishing and exploding gradient problems. LSTM unit is consisting of a cell, forget gate, an input gate and an output gate.

$$f_i = \sigma(W_f x_i + U_f h_{i-1} + b_f) \tag{6}$$

$$i_i = \sigma(W_i x_i + U_i h_{i-1} + b_i) \tag{7}$$

$$o_i = \sigma(W_o x_i + U_o h_{i-1} + b_o) \tag{8}$$

$$c_i = f_i * c_{i-1} + i_i * \tan h\,(W_c x_i + U_c h_{i-1} + b_c) \tag{9}$$

$$h_i = o_i * \tan h\,(c_i) \tag{10}$$

Here, h_i represents hidden state, c_i is the central state, o_i is the output gate, i_i is the input gate and f_i is the forget gate.

Fig. 2 illustrates the combined architecture of the hybrid two-stage LSTM-SVM model. Extracted features are given to input layer. The hidden layer of the LSTM consists of N layers. These layers will get interacted and given to the fully connected layer. LSTM is similar to RNN, but it has only one tanh layer. The LSTM has two tanh layers and 3 sigmoid layers. The output from the hidden layer is given to the fully connected layer. The softmax layer of the LSTM is replaced with SVM for classification. Softmax layer is a softmax function, which is mainly used for multi-class classification. The SVM first finds hyperplanes that differentiate the classes to perform classification task. Thus, the prediction of sentiment class will be acquired as an output from the classifier.

c) Incremental Learning: In incremental learning, first trained-net produces a classification of sentiment with a set of extracted features. The output from the trained-net (X) will be sentiment classes e.g. happy, sad, shock and angry as shown in algorithm.

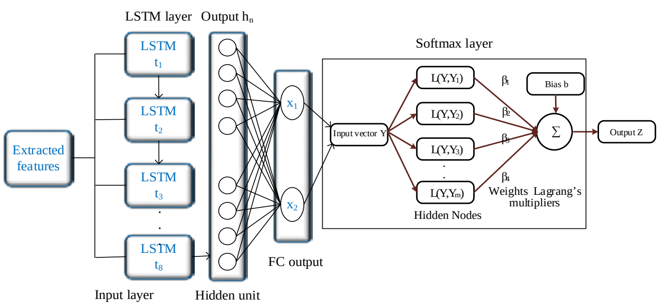

Fig. 2. Hybrid Two-Stage LSTM-SVM Architecture.

Then for incremental learning the new features (Y) are added to the trained-net (X), it produces an updated trained-net output (Z=X+Y). This updated trained-net will predict the new features according to the sentiment classes such as happy, sad, shock and angry. Likewise, the new classes (N) are added to the trained net (X) for producing an updated trained-net (N1), these updated trained-net (N1=X+N) will be addition of new classes and existing classes. The new class consists of confident and confused and the existing class consists of happy, sad, shock and angry. These classes are added and produce an updated trained net (N1) output, which consist of happy, sad, shock, angry, confused and confident as mentioned in Fig. 1.

IV. Result and Discussion

The acquired datasets consists of special characters, uppercase and keywords. These characters in the sentence are extracted by using the pre-processing technique, which consist of spell correction, tokenization, stop word removal, splitting and lemmatization. Next process is feature extraction for removing the unwanted words because large data will take more processing time, to overcome this issue the dimensionality reduction is used. The extracted features from the countvectorizer and dimensionality reduction are given to the hybrid two-stage LSTM-SVM classifier for sentimental analysis.

Algorithm: Incremental Hybrid Two-Stage LSTM-SVM Classifier for Sentiment Classification

Input raw dataset = A

```
For all data in dataset

   #Pre-processing (A)
    A1 = Splitting (A) // Sentence splitting into words for processing
    A2 = Tokenization (A1) // Breaking sequence of strings into pieces
    A3 = Stop word removal (A2) // stop words such as “the”, “an”, “a” are removed
    A4 = Lemmatization (A3) // Changing words with different derivatives
    A5 = Spell correction (A4) // auto correction of noisy to proper words for misspelled words

   #Feature extraction
    A6 = Countvectorizer (A5) // Conversion of string to numerical
    A7 = Dimensionality reduction (A6)

   #Hybrid Two-stage LSTM-SVM Classifier
     L = LSTM (A7) // Numerical value from Countvectorizer is classified with LSTM
     S = SVM (L) // Last layer output of LSTM is classified with SVM

   #Incremental Learning
     Trained-net = S
     For (i=0, i=i+n, i++) // Initial value = 0, number of features = n, new features = i
      {      Z=S+i         // Adding trained-net and new features, Updated trained-net (Z)
      }
     For (j=0, j=j+n, j++) // Initial value = 0, number of features = n, new classes = j
      {      N=S+j         // Adding trained-net and new classes, Updated trained-net (N)
      }
```

Output: Prediction of sentiment classes based on reviews with incremental learning

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a) Datasets: For Model evaluation four separate datasets were used. 1) Sentiment Labelled Sentences Data Set [28]: in this dataset, sentences are selected from three different websites: {imdb.com, amazon.com, yelp.com}. From each website, 500 positive and 500 negative sentences are randomly selected. 2) Large Movie Review Dataset [29]: this dataset is taken from Kaggle - IMDB dataset of 50000 movie reviews. 3) Amazon product review dataset [30]: this dataset contains product reviews (ratings, text, helpfulness votes). 4) The Yelp dataset [31, 32] is a subset of reviews, businesses and user data for use in personal, academic purposes and educational. This dataset consists of 8,635,404 reviews, 160,585 businesses, 200,000 pictures and 8 metropolitan areas.

Fig. 3 illustrates the extraction of input in the prepossessing step. Datasets is acquired and converted to lower case. Sentence will be extracted by the special character removal, which removes the special characters such as ‘@’, ‘#’, ‘_’. Then splitting and localization process will take place, this is used to split each and every word and localize it. After splitting and localization, the next step is removal of the stop words such as is, are, a, an, the etc. These are the steps involved in the pre-processing technique and the next step is data partitioning and feature extraction. The feature extraction is implemented by the Yake tool [33]. The extracted features are classified by a two-level classifier, which is a hybrid model that is combination of LSTM and SVM. The performance of state-of-the-art existing feature selection approaches is compared with proposed feature selection process. The performance attained using Accuracy, Precision, Recall, F-1 score, Specificity, False Negative Rate (FNR), False Positive Rate (FPR), Negative Predictive Value (NPV) and Error.

Table I and Table II illustrate the results obtained on datasets 1, 2, 3 & 4 for various metrics using the existing and proposed sentiment classification model. The values for parameters such as Error, FNR, FPR are smaller as compared to existing techniques and the metrics such as accuracy, precision, recall, F-1 score and NPV are greater as compared to existing techniques. The below section will explain graphical representation for the comparison of proposed and existing models.

Input Review	Output Tokens
The food is always great here. The service from both the manager as well as the staff is super. Only draw back of this restaurant is it's super loud. If you can, snag a patio table!	'food', 'always', 'great', 'service', 'manager', 'well', 'staff', 'super', 'draw', 'back', 'restaurant', 'super', 'loud', 'sang', 'ratio', 'table'
This place used to be a cool, chill place. Now its a bunch of neanderthal bouncers hopped up on steroids acting like the can do whatever they want. There are so many better places in davis square where they are glad you are visiting their business. Sad that the burren is now the worst place in davis.	'place', 'used', 'cool', 'chill', 'place', 'bunch', 'neanderthal', 'bounce', 'hoped', 'osteoid', 'acting', 'like', 'whatever', 'want', 'many', 'better', 'place', 'davis', 'square', 'glad', 'visiting', 'business', 'sad', 'burden', 'worst', 'place', 'davis'
The setting is perfectly adequate, and the food comes close. The dining chains like Chilis and Victoria Station do barbecue better. It's no surprise you can always pick up coupons for Linwood at restaurant.com.	'setting', 'perfectly', 'adequate', 'food', 'come', 'close', 'dining', 'chain', 'like', 'child', 'victoria', 'station', 'barbecue', 'better', 'surprise', 'always', 'pick', 'coupon', 'linwood', 'restaurant', 'com'

Fig. 3. Input and Output Obtained after Pre-Processing.

TABLE I. PERFORMANCE BASED COMPARISON FOR DATASET BETWEEN PROPOSED AND EXISTING TECHNIQUES ON DATASET 1 & 2

Performance Metrics	Techniques									
	DATA 1					DATA 2				
	RF	ANN	SVM	LSTM	LSTM-SVM	RF	ANN	SVM	LSTM	LSTM-SVM
Accuracy	0.42	0.68	0.75	0.78	0.85	0.80	0.82	0.84	0.84	0.92
Error	0.58	0.32	0.25	0.22	0.15	0.20	0.18	0.16	0.16	0.08
Precision	0.20	0.40	0.49	0.66	0.88	0.78	0.74	0.76	0.80	0.85
Recall	0.18	0.15	0.30	0.45	0.71	0.25	0.36	0.40	0.68	0.78
Specificity	0.50	0.78	0.82	0.84	0.96	0.84	0.86	0.86	0.88	0.93
F1_Score	0.70	0.76	0.84	0.88	0.92	0.70	0.76	0.82	0.86	0.91
Negative Predictive Value (NPV)	0.52	0.78	0.82	0.84	0.92	0.84	0.84	0.89	0.93	0.94
False Negative Rate (FNR)	0.32	0.30	0.29	0.25	0.20	0.20	0.20	0.17	0.14	0.05
False Positive Rate (FPR)	0.23	0.17	0.09	0.06	0.05	0.35	0.30	0.22	0.17	0.10

TABLE II. PERFORMANCE BASED COMPARISON FOR DATASET BETWEEN PROPOSED AND EXISTING TECHNIQUES ON DATASET 3 & 4

Performance Metrics	Techniques									
	DATA 3					DATA 4				
	RF	ANN	SVM	LSTM	LSTM-SVM	RF	ANN	SVM	LSTM	LSTM-SVM
Accuracy	0.63	0.68	0.68	0.77	0.86	0.60	0.73	0.76	0.78	0.89
Error	0.37	0.32	0.32	0.23	0.14	0.40	0.27	0.24	0.22	0.11
Precision	0.64	0.69	0.70	0.71	0.87	0.60	0.76	0.76	0.83	0.90
Recall	0.63	0.68	0.69	0.69	0.87	0.60	0.73	0.75	0.71	0.89
Specificity	0.63	0.68	0.69	0.84	0.86	0.60	0.73	0.76	0.85	0.89
F1_Score	0.67	0.69	0.71	0.75	0.91	0.70	0.73	0.74	0.83	0.86
Negative Predictive Value (NPV)	0.68	0.69	0.72	0.77	0.85	0.71	0.73	0.81	0.83	0.89
False Negative Rate (FNR)	0.30	0.21	0.20	0.15	0.10	0.24	0.20	0.17	0.13	0.08
False Positive Rate (FPR)	0.39	0.31	0.29	0.19	0.12	0.20	0.19	0.16	0.10	0.08

Fig. 4 illustrates the comparison metrics as mentioned in Table II and Table III, for proposed approach with the existing approaches. In this the existing approach such as LSTM, SVM, ANN, and RF are compared with the proposed approach of hybrid two-stage LSTM-SVM. It is observed that hybrid two-stage LSTM-SVM performs well in comparison with approaches.

Table III illustrates the comparison of performance metrics for incremented classes and features on the proposed model. Fig. 5 illustrates the accuracy comparison of incremented values for the proposed model. In this figure, the performance metrics for three class 50 features is smaller compared to incremented three class 75 features. The performance metrics of the incremented five class 50 features is smaller compared to the five class 75 features. From this, the incremented class and features of the proposed model attains a best performance metrics.

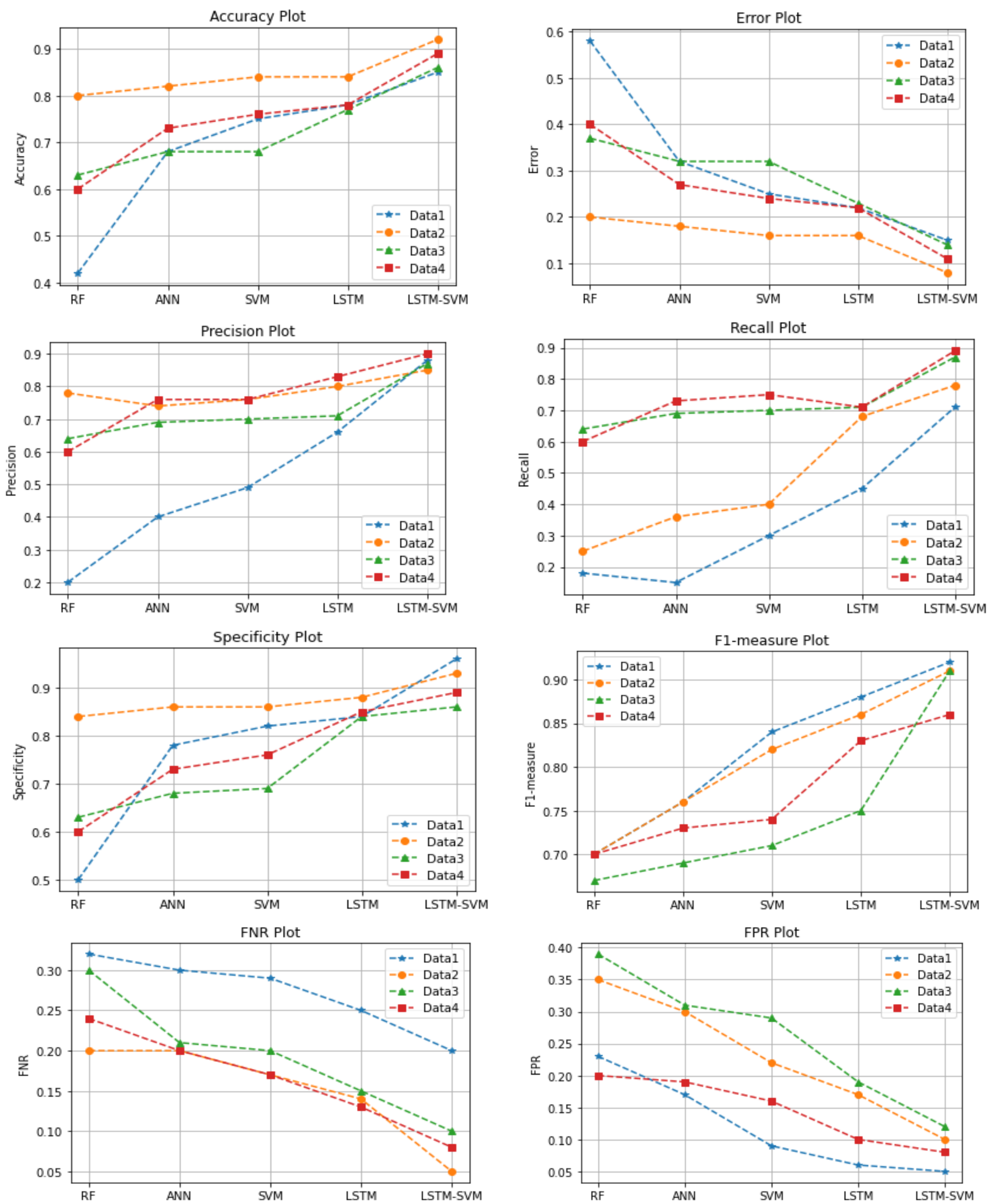

Fig. 4. Comparison of Accuracy, Error, Precision, Recall, Specificity, F1-Measure, FNR and FPR Metric.

TABLE III. COMPARISON OF PERFORMANCE METRICS FOR INCREMENTED CLASSES AND FEATURES ON THE PROPOSED MODEL

Proposed method	**3 class with 50 features**	**3 class with 75 features**	**5 class with 50 features**	**5 class with 75 features**
Accuracy	0.895	0.99	0.85	0.88
Error	0.11	0.01	0.15	0.12
Precision	0.83	0.98	0.51	0.61
Recall	0.80	0.98	0.53	0.63

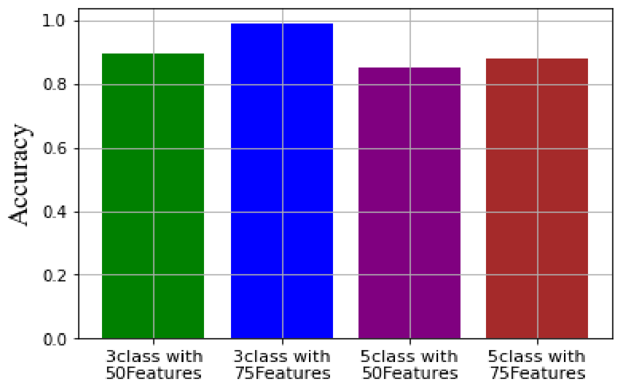

Fig. 5. Comparison of Accuracy Metrics for Incrementing Features and Incrementing Classes.

V. CONCLUSION

This paper aims to design best sentiment analysis for social media posts and review comments. Many researchers are trying to utilize the large datasets for sentiment analysis but the performance of conventional techniques is not satisfactory. In this technique, features are extracted and converted by the countvectorizer, then for classification a hybrid two-stage LSTM-SVM model is used to predict sentiments. The proposed hybrid two-stage algorithm is validated and compared with the state-of-the-art existing sentiment classification technique. The comparison analysis revealed that the proposed model has excellent performance metrics. The accuracy of the proposed model varies according to the incremental leaning, the accuracy for three class 50 and 75 features is 89 and 99 then, the accuracy for five class 50 and 75 features is 85 and 88. This analysis reveals that the incremented class and features attain a better accuracy.

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