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Sindhi Text-Based Students Sentiment Analysis Using Convolutional Neural Network

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Abstract
Current generation especially the teenager students are using Social Media (SM) platforms at an extreme level even the sentimental angles are too discussed there. In the province Sindh, students mostly prefer to text the message in origin of their mother tongue i.e. Sindhi lexicon for sharing their views regarded politics, religions, sports, education etc.All these sentimental conveys are important for enhancing the academic capabilities.In this research paper, approach is broken down into multiple phases comprising of number of WhatsApp chat, lexicon generation, dataset tokenization, Convolutional Neural Network (CNN); all based on respective sentiments.To validate the experimentation process at standard level. 100 WhatsApp data chats were collected from different levels of students and divided into four categories.The CNN Model is used for sentimental classification. Accuracy, Precision, Recall and F-Score are the four parameters used for model evaluation. The model provides 0.874% accuracy, 0.883% recall, 0.863% precision and 0.745% F-Score.

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1 Introduction
People use to share their precious and personal data on Internet. Among them a lot sentimental data are available on the platform like SM. Mostly university students use SM on owing to the provision of smart phones i.e. they may have an easy approach to number of SM sites [1]. Moreover, to perform the sentimental analysis on data available on the SM sites, various robust tools, techniques, methods and well-recognized approaches are available and working collaboratively [2, 3]. Many models and frameworks are also proposed and implemented by the researchers of Sentiment Analysis.

The accessible research studies substantiated that the student has low academic achievement who spends most of the time on SM. In general, the SM has incidental and beneficial consequences now it is up to the students to correctly coordinate the accessible SM networking sites [4]. The term sentiment analysis (SA) refers to the process of purification through data, information, ideas, reviews etc. posted by users [5]. To perform SA on text messages conveyed through Sindhi language is challenging as it is rich in phonology, morphology and orthography as compared to other languages.

For the last two decades, Sentiment Analysis (SA) is a popular and demanding field because of its usage in numerous applications among different organizations and departments. The academic institutions are attempting to analyze the students and teachers feedback [6]. SA is important in providing the best predictions of the educational activities going on within a university. This is a very crucial feature since SA can lead to more precise and reliable forecast, specifically in the field of education for increasing and developing the quality of learning level activities of the students. SA (subfield of NLP) is the emerging research area. , and is selected in this research study. To evaluate the students' academic performance, this research study performs SA on WhatsApp-based small chat messages written in Sindhi.

2 Literature Review

The SA is an emerging field, enables computing processes to analyze individual's sentiments.SA can be categorized into three groups i.e. neutral, positive and negative. The existing literature mainly focused on the perceived text-based SA, enhancing students' academic performance. Aherdoost [2] analyzed a number of research published articles in between 2012 to 2022, and presented a summarized description of each of the selected articles.

Arabic is one of the famous and rich languages which is spoken by millions of people in different countries around the globe. Al-Saqqa [7] established the performance of ensemble ML techniques, effectively used to classify the sentiment polarity of the Arabic text that has been gathered. In this case, the majority voting approach was applied in conjunction with the selected classifiers including; Support Vector Machine (SVM), Decision Tree Naïve Bayes and K-Nearest Neighbor (KNN). Another research work was done by Alowaidi [8] in which the author developed a semantic model for SA using Arabic Tweets. This work proposed a model which is still to be developed from the techniques of supervised ML and semantic analysis. The text usually used in the different dialects was employed for developing the SA of the students with the help of the ML approaches. The experimental results available in the study of these researchers confirmed that, among all the classifiers, Bernoulli Naïve Bayes classifier is the best because the authors recorded the general efficiency of 82% in one data set and 87%. This was done with an accuracy of 7% using the other developed dataset with SVM classifier.

Thanh [9] adopted a combine method of ML and lexicon based approaches for the purpose of SA and for the purpose of calculating better accuracy of the experimented techniques. Shan [10] proposed an SA model based on CNN-BiGRU to classify the text circulated through SM siteson large scale. The amounts that were computed to the researchers were 94. 09% accuracy using the above mentioned research methodology. The Kong [11] used an enhanced CNN model for the study that was conducted on the chosen problem. The models suggested an organizational structure for SA and was adopted to develop sentiments dictionary. Scholar's highlighted different presentation based decisions of CNN and subsequently evaluated the composed framework with beforehand developed techniques in terms of recall and accuracy-based evaluation techniques used for the purpose of SA.

For the purpose of SA, Sodhar [12] has carried out statutory Aspect-Based Sentiment Analysis based statistical study.An online accessible Sindhi newspaper namely AWAMI AWAZ was used as the source of data collection.Similarly, Hammad[13] performed SA on Sindhi text using supervised ML algorithms. Sindhi language based tweets were used as data input in the proposed research. The proposed methodology involved assigning the negative and positive text polarity from the predefined lexicon to the selected tweets Therefore, researchers formulated two classes out of the textual data. To extract Sindhi text some important preprocessing operations were carried out on the collected raw Sindhi text including extra white space removal, non Sindhi words and punctuations removal. After that, tokenization process was performed in order to separate the words. After the process of labeling and cleaning the data on the Sindhi language tweets datasets, the most advanced machine learning algorithms were implemented on collected text-based datasets. The results of each classifier evaluated separately where scholars discovered that KNN and DT were the most effective in classifying Sindhi Language-based sentiments.

Deep Learning has been quite familiar in the previous few years, especially in the arena of NLP as most academics have leveraged recent advances in SA. The Mahendhiran [14] aimed at the different ways to categorize the audio and video files into three categories such as neutral, negative, and positive. Different methods of classification were adopted like KNN method, NN model, Naïve Bayes, Random forest. The researcher found the deep learning based classification algorithm most effective for SA. The roman text of the Urdu language was also experimented for analysis of the sentiments, Ghulama [15] implemented Deep Neural Long-Short Time Memory network to determine sentiments expressed in Roman Urdu. Similarly, Omer [6] performed SA for students receiving online education using ML and Triple Likert method.0.775 ratio of accuracy was determined using logistic regression based on the collection of feedbacks of 6059 students.

Jimenez [16] presented an SA model for comments of the students. These are comments that obtained based on the proficiency of the professors. To obtain comments data, members of the university were asked to complete a survey in the year 2019 and 2020. Furthermore, learning experience of the students was assessed by Lazrig [17] wherein, 333 students' data were used. Labeling the three fundamental feelings of neutral, negative and positive as the feelings were considered to gain the experience. The sentiment classification performed with two ML and five Non-Learning approaches. With the naïve Bayes classifier, 98% accuracy achived without any neutral sentimental data. To develop various SA applications, the mentioned ML techniques are implemented, and thus Singh [18] also employed unsupervised methods collectively with dictionary-based techniques of SA which offered maximum time complexity. Bordoloi [19] also proposed the future directions and application of SA.

3 Methodology

The first stage of this research work entails Sindhi corpus collection. To collect data, severalstudents' WhatsApp groups belonging to the Institute of Computer Science (ICS), Shah Abdul Latif University were used. The chat messages in Sindhi text format that were obtained were believed to encompass the linguistic aspect during the data collection process thus enabling the use of SA using the written Sindhi sentences. As a result of corpus collection, a vast database is created after the process of language collection. The dataset is the text input into the ML process, is an important component in this research.Besides, several text pre-processing tasks are performed on the collected text. Therefore, there are numerous procedures applied for data sorting, including data reduction, which is the lack of needless information.

An important phase of the research study is the text tokenization. Due to the fact that space usage is irregular within the text in languages with limited properties such as Sindhi, It is difficult to process the text using NLP approaches. Therefore, text tokenization becomes an important phase of the research study. Mahar [20] proposed a tokenization methodology for NLP which is adopted in this research as well. Sindhi lexicon is required for SA. A Sentiment Lexicon is a list of words that contain opinions that have been tagged by the polarity for instance; positive/negative and the strength of the sentiment. The entire Sindhi corpus is then tokenized and analyzed using NN approach. To calculate the overall results of the model, the evaluation is done at the end of this research, in an effort to see where the system stands regarding its efficiency. CNN was employed for SA while it was designed using PYTHON programming language. It is further illustrated in the complete research model presented in Figure 1.

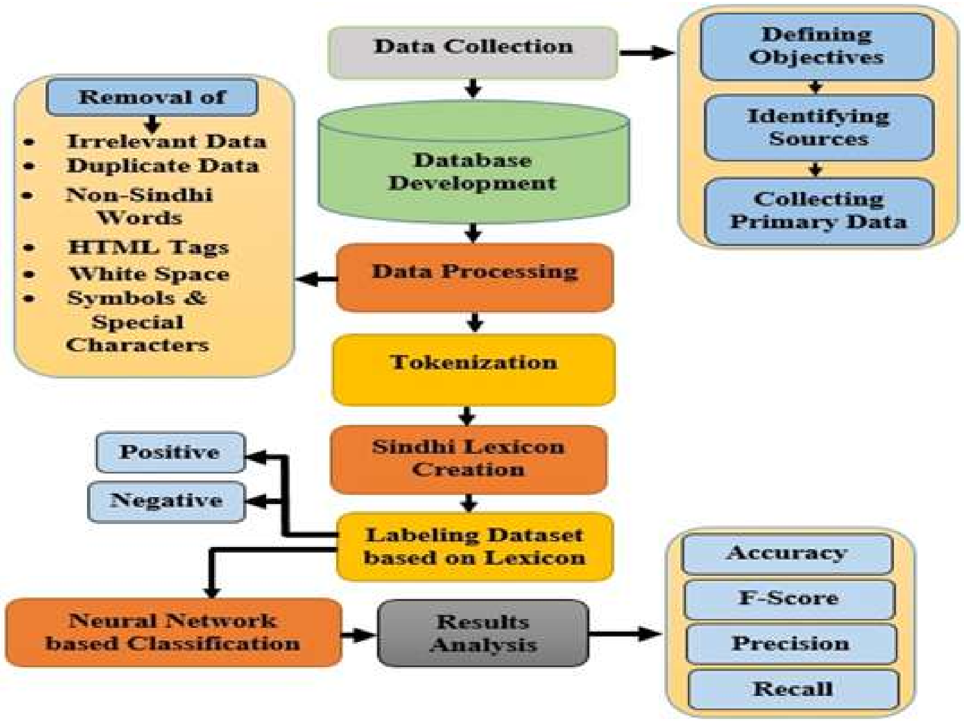

Figure 1. Flowchart of Research Methodology

4 Sindhi Corpus Collection

Sindhi language-based corpus is created in this research work. Data from textual messages exchanged among students was driven for corpus collection. The collected data can be claimed to be more real and natural. The ICS offers two undergraduate programs i.e. BS in Information Technology and B.S in Computer science. Each program is further divided into four batches such as Part-I, Part-II, Part-III, Part-IV. It is also discovered that boys' and girls' groups are formed separately.Depending on the above averred arguments, different WhatsApp groups of students enrolled in above defined programs were sampled for data collection. Most of the time, students employed small WhatsApp chat messages to share their ideas, and emotions regarding various academic activities like assignments, projects, exams and others. Thus, most of the students compose their messages in Sindhi language.

Separate WhatsApp groups were created for boys and girls studying in BS (Computer Science) and BS (Information Technology) (Part-I to Part-IV). Therefore, to validate the dataset chat messages from different groups of boys and girls are considered. The specifics of WhatsApp include a choice of the total 100 chat messages as an object of experiments. From the students of BS (Computer Science), part-I, 13 messages were collected, the total number of 12 and 10 chat messages were collected from the students of part-II and part-III respectively. The highest number of 14 small chat messages is received from the students of part-IV. Similarly, messages are collected from the students of BS (Information Technology). The total number of 12 and 14 messages was gathered from the class part-I and part-II. 13 chat messages are received from the students of part-III and 12 messages are collected from the students of part-IV.

The use the word format to create the database in order to perform preprocessing operations on them. The collected dataset further divided into three sets for analysis and testing requirements which are as follows. Group-I contain syllabus related reviews and comprised of 32 messages, Group-II consisted on teacher-related comments and comprised of 35 messages and Group-III comprised of 33 messages which is contain reviews regarding academic activities.

4.1 Sindhi Text Preprocessing

The data processing techniques applied to structure the data for example by eliminating unnecessary or unwanted data. The data was also normalized to maintain standard in the concern of collection. This calls for the erasure of every HTML links, hashtag sign, non-Sindhi words, spaces, special characters such as emoticons and symbols which are not relevant to the analysis from the text. Nonetheless, another model of tokenization suggested by Mahar [20] is used for performing the tokenization task.

4.1.1 Lexicon Development and Labeling

In order to complete the SA, Sindhi lexicon developed with the assistance of an expert in the field. As it is noted earlier that data was collected through the WhatsApp chat groups. Consequently, the study managed to collect 300 WhatsApp messages with happy and sad related feelings. 5379 words in total, 3821 of them labelled, constitute the recorded communications and the rest of the words, whose meaning was unspecified, were not annotated. Labeling each word or phrase Happy or Sad to represent sentiment is starting process in constructing a lexicon in which sentimental words of Sindhi text is stored for upcoming processes. The procedure utilized to create a sentiment lexicon generation process with two main parameters of Frequency Positive (FP), Frequency Negative (FN) and is demonstrated by a simplified equation as defined below:

Lexicon Score = (FP – FN) / (FP + FN).

FN refers to the number of times that a word or phrase is used in depressing articles while FP corresponds to such use in cheerful articles. The number of negative incident occurrences is subtracted from the positive incident occurrence and the dividing sum total of both positive and negative is made to arrive at the Lexicon Score. 'Happy' group of Sindhi words gets positive score, 'SAD' group of Sindhi words gets negative score while words which are emotionally neutral, get middle values or no emotional score. The Lexicon Score has a specific range like, ranging between -1 and +1 and passing / crossing -1 typically indicating positive-sentiment words, crossing / passing 0 indicates negative-sentiment words and anything equalling 0 indicates neutral sentiment words. Moreover, addition of the lexical scores yields the final sentiment score of the given text.

The complex POS tagger for Sindhi language is missing thus in the current work, so manually process of tagging is carried out for the Sindhi words based on available POS taggers of English language. The spaCyPOS tagger is sued to define the tag of a particular word which makes it possible to classify the given Sindhi terms to their respective POS tag. Moreover, features were derive which are most coherent with the class label from the labeled reviews based on feature weights. This is not within the function since the existing word is discard or terms of the lexicon which have been identified in the previous phases. This is done based on sentiments score, which is calculated by adding up all the sentiments of the relevant words or phrases in the text then label the text with either 'Happy' or 'Sad'. In the meantime, the sentiment score was changed based on some syntactic features such as the addition or subtraction of modifiers and omissions, and the addition that in Sindhi can either diminish or enhance the feeling of a word or a phrase. The Adjectives and verbs are kept because most of the other POS that excluding represent opinion. The Eq. 1 is used to assign a sentiment score to word, w.

SentimentScore(w) = PMI(w,pos) – PMI(w,neg) (1)

In the context, PMI(w, pos)represents the PMI score of a word for the class happy whilePMI(w, neg)represnts PMI score of a word for the class sad. Following equation is used to calculate the the sentiment intensity (SI) of w:

SI(w)=SentimentScore(w)/(PMI(w,pos)+PMI(w,neg)) (2)

Finally, in order to decide whether the emotion score in average is higher or lower, it has to be compared to a threshold value. The labeling approach is also discussed and refined through an incremental optimization process based on a comparison of tagged information versus actual data or samples manually labeled. The match with the threshold value is made between the sentiment intensities of words and to detect sentiments that comprise terms from the labeled assessments. When the sentiment intensity, w, of a word increases beyond cut off (0.5) then it is taken to be positive sentiment and while it is number 5 and count it as a happy term. The way that a term is classified depends with the strength of its sentiment as where a sentiment strength less than -0.5 is considered as sad sentiment. If required, the lexicon is modified or combined using other new rules or a different approach to enhance the effectiveness of labeling technique for the Sindhi text.

5 Implementation

It will be used for SA, and has been trained by using python. Generally, there are three steps that are often followed in order to achieve the certain goal. First, the following algorithm for the process of the students' SA with the usage of the different effective libraries of Python is introduced below.

Algorithm 1. Steps to Implement the Neural Network with Three Layers

1: **Step-1:** Import the Keras library for deep learning.
2: **Step-2:** Import `Sequential` and `Dense` classes from the Keras module.
3: **Step-3:** Create a `Sequential` model object.
4: **Step-4:** Add a `Dense` layer with 64 neurons, ReLU activation function, and input dimension of 300.
5: **Step-5:** Add a `Dense` layer with 10 units and apply `Softmax` as the activation function.
6: **Step-6:** Train the model with the loss function `categorical cross entropy`, optimizer `stochastic gradient descent`, and accuracy as a metric.
7: **Step-7:** Import the `numpy` library for matrix operations.
8: **Step-8:** Generate random data using `numpy.random.rand()` with a shape of (1000, 300).
9: **Step-9:** Prepare data labels (1000 units in a column, 19 in a row) using `numpy` and `keras.utils.to_categorical()`.
10: **Step-10:** Fit the model for the generated data and labels for 10 epochs using a batch size of 32.
11: **Step-11:** Perform classification on the data.

Many computational models have been used for the task of SA, among them NN is one of the simplest forms of learning that takes place under the greater category of machine learning, which has a branch known as deep learning. The model based upon the above theory comprises of several layers such as the Input Layer, The Convolutional, The Pooling, The Flatten, The Fully Connected and finally the Output Layer. CNN is a specific type of neural network architecture which was intended to perform categorization of Sindhi text using a neural network model. Figure 2 is the illustration of CNN model.

Figure 3 depicts the process of execution, displaying the whole process of SA employing the CNN model. Initially, the system executed 100 epochs, results are displayed which shows the accuracy and error loss.At the 809th epoch out of 100 of the 15th iteration, the developed model provide optimal result with 87

5.1 Evaluation Techniques

Another practical approach in the field of ML is called confusion matrix (CM) which enables researchers to determine the accuracy, precision, recall, and f-score [21]. Eq. 3, Eq. 4 and Eq. 5 evaluate the formulas for accuracy, precision and recall respectively. CM matrix helps in understanding the errors which are produced by the particular classification algorithm along with the limitations of the technique that has been used. In each column of CM, the number of the occurrences of the predicted class of the inputted data is shown.

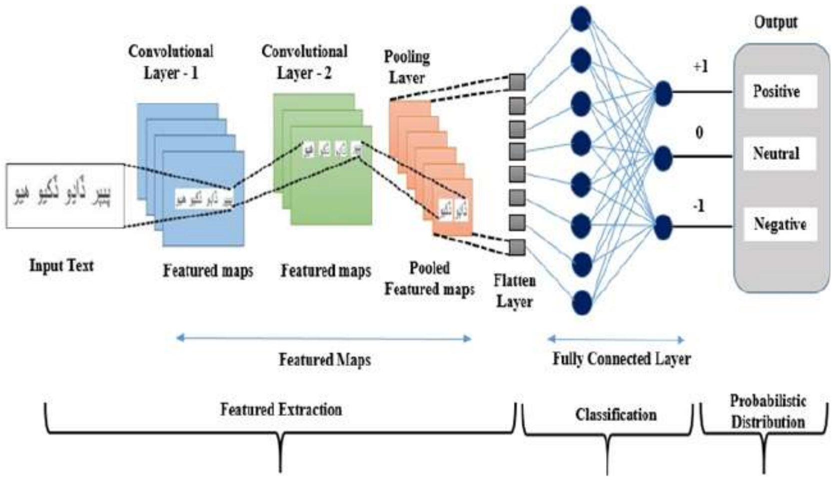

Figure 2. Composed Framework of CNN for Text-Based SA

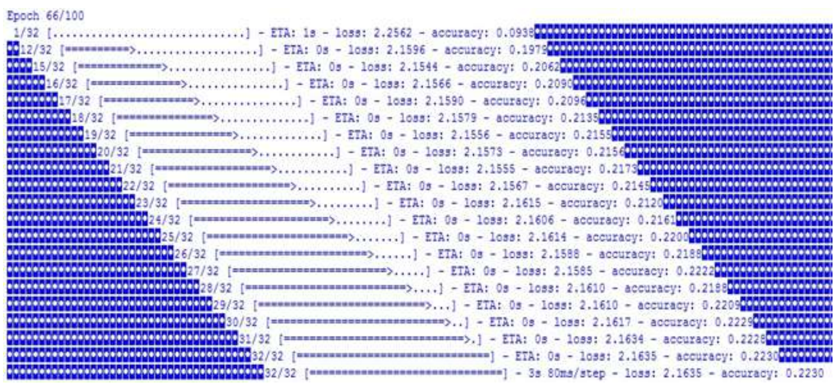

Figure 3. Execution Process of CNN Model in Python

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

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

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

Consequently, this research seeks to analysis the sentiments of the students by interpreting the small chat messages that the students have been sharing on different WhatsApp groups. To accomplish this task, experiments are made with 100 messages from the WhatsApp chat.These chat messages are further distributed in four classes including the first 25 messages, 26 – 50 chat messages, 51 – 75 chat messages and 76 – 100 chat messages. The distribution of the chat messages is useful in an independent assessment of the respective values of system accuracy, precision, recall and f-score.

6 Results

With the evaluation techniques as described above the results are calculated and measured. The assessment of the proposed CNN model and algorithm is required to calculate the efficiency of the system regarding sentiment analysis from WhatsApp chat messages.

6.1 Accuracy Performance of CNN Model

Experiments performed with the developed model and accuracy measured. Initially, experiments performed on the first 25 chat messages and results generated. Figure 4 shows the attained result of experiments performed with first 25 chat messages. As depicted in Figure 5, the proposed model with four chat messages successfully achieved the high accuracy. Using the message of M-13 system was able to establish the accuracy of 0. 974 while the corresponding accuracy of 0.984 is obtained with message from M-18 and M-19. Besides, the highest accuracy of 0.986 is achieved with M-20 and on the contrary the lowest accuracy of 0.764 is received with chat messages of M-25. However, the cumulative accuracy received is0.852.

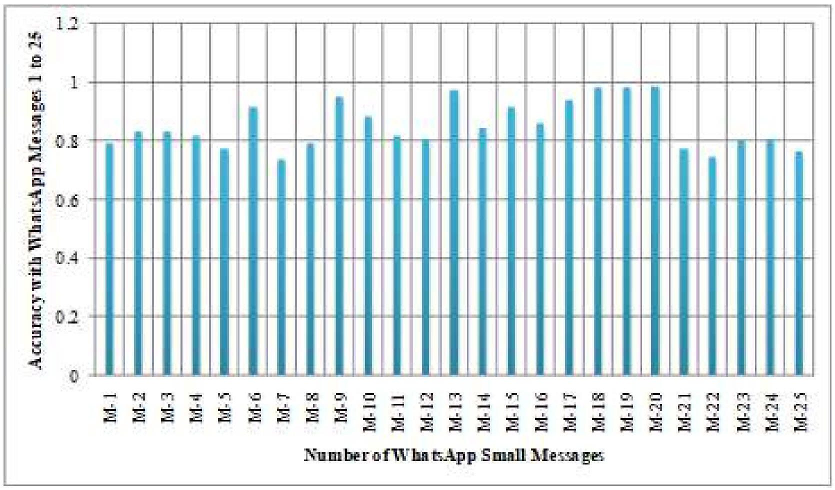

Figure 4. Measured Accuracies with 1 to 25 Chat Messages

Next experiments are performed on the 25 representative chat messagesfrom M-26 to M-50. The computed accuracies are indicated as follows in the graph shown below in Figure 5. While focusing the accuracy of individual chat message, it is observed that M-32 and M-33 gives the highest accuracy i.e., 0. 991. Both the messages contain only 2 words with 1 sentiment word each. However, M-36 message provide the least accuracy of 74.5

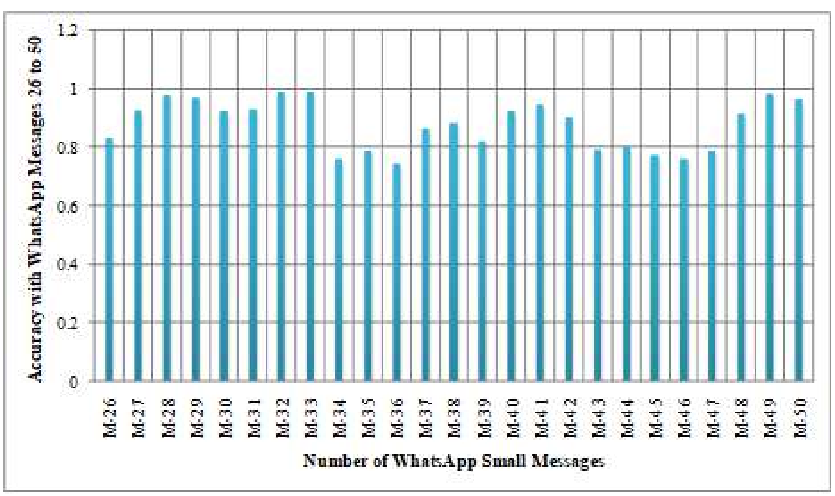

Figure 5. Measured Accuracies with 26 to 50 Chat Messages

The messages from M-51 to M-75 are also tried in respect of benchmarking the performance accuracy of the proposed CNN model and the developed algorithm. The percentage of calculated accuracy of the mentioned chat messages is shown in the Figure 6. The average accuracy 0.845is attained with the messages from M-51 to M-75.

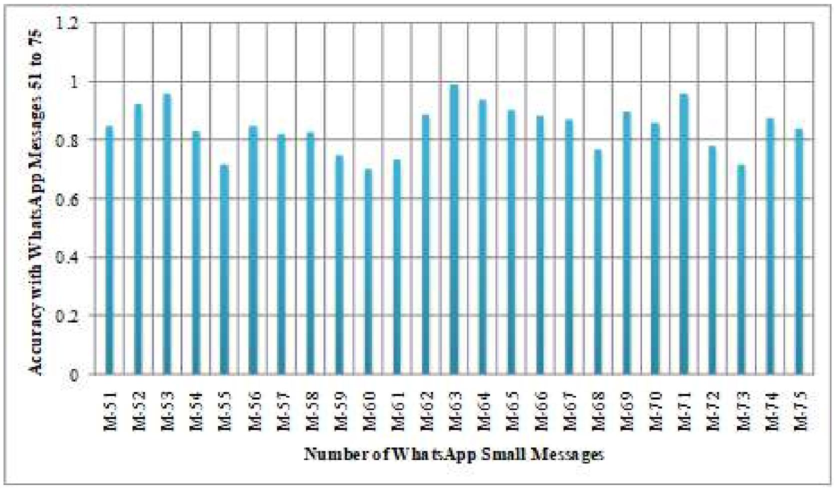

Figure 6. Measured Accuracies with 51 to 75 Chat Messages

Finally, every message from M-76 to M-100 was taken for experiments and provided the mean accuracy of 0.919 and is considered as the best accuracy among all messages. Figure 7 below shows the results achieved with messages M-76 to M100.

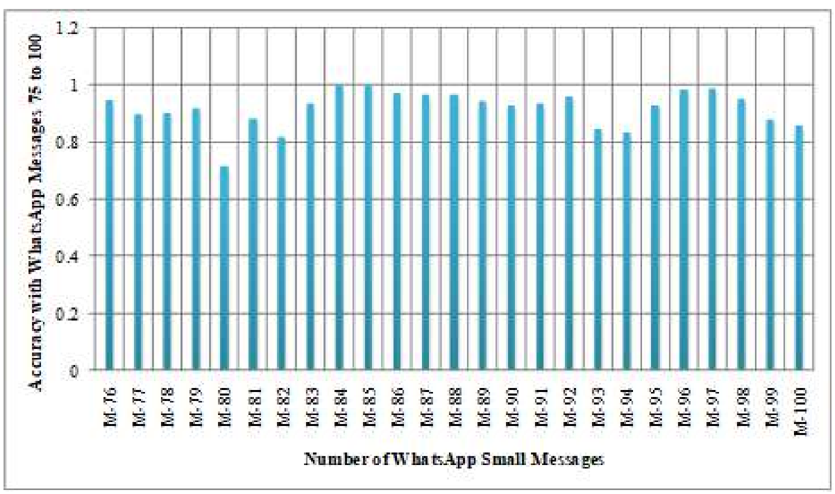

Figure 7. Measured Accuracies with 75 to 100 Chat Messages

6.2 Precision Performance of CNN Model

The level of the research findings and the reliability and genuineness can be used to express the precision. The reliability of each message sent through chat after computing the accuracy results via the students' SA system is measured. Initially, the WhatsApp chat messages between M-1 and M-25 are collected for testing. Figure 8 shows the calculated precision results. The chat message M-20 yields the highest precision score of 0.980, while the two chat messages M-18 and M-19 yield the next-highest precision score of 0.979 and 0.978, respectively. Similarly,

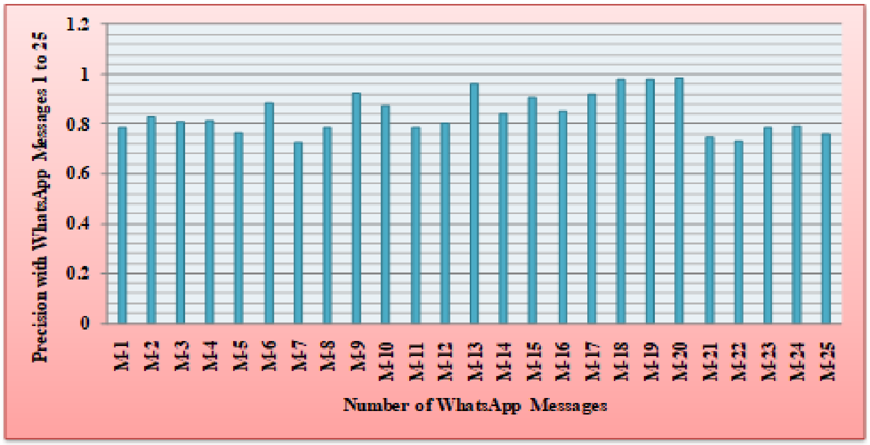

Figure 8. Measured Precisions with 1 to 25 Chat Messages

chat message M-7 yielded the lowest exactness of 0.728. The computed precision percentages are generally higher than 0.80. Using these, an average precision of 0.839 is estimated these twenty five chat messages.

The next twenty-five chat correspondence, or M-26 to M-50, are selected for experimentation in a precision calculation. According to the developed sentiment analysis system, chat message M-33 yields a highest exactness of 0.988, while chat message M-32 yields a closest precision of 0.983. It is observed that the best precision results come with the fewest conversation words and sentiment words. The value of precision decreases as the word count increases. As it arrived at the precision of 0.736 using M-36, where there are 10 total words and 4 sentiment-expressing words. The total precision value determined by this specific set of chat messages is 0.869. In Figure 9, it can find out the calculated precision against each chat message.

The chat information from M-51 to M-75 are used to determine the precision accuracy of the system. Figure 10 demonstrates that chat message M-63, which has an excellent rating of 0.984, provide best result. The current chat message has three words in total, but the selected message only has one sentiment word. With 15 words and 1 emotion word in chat message M-60, the precision of 0.700 is computed. These particular messages are used to calculate the typical accuracy of 0.833.

By applying the students' WhatsApp chat messages, the precision progress from M-76 to M-100 is calculated. Figure 11 shows the calculated precision results. Upon inspection of the calculated the precisions, it is discovered that M-85 yields the best result, 0.992. A different suitable result, 0.984, is computed using chat message M-97. Due to the extended message, the interaction with M-80 yielded an inferior precision value of 0.708. With these particular chat messages, the average precision value is 0.911. On average, these discussions are used to calculate with the finest accuracy. The finalized result calculates that CNN model is much suitable and works more accurate with Sindhi Language.

6.3 Recall Performance of CNN Model

In circumstances in which False Negative outcomes are far more costly than False Positive results, the recall an assessment technique is crucial. Initial 25 chat messages, M-1 to M-25, tested. Together, they produced a recall outcome of 0.861. Figure 12 displays the computed value of recall for every chat message. The figure demonstrates that WhatsApp communications M-5, M-21, and M-25 yield the most negative recall results, while M-15, M-19, and M-20 yield better recall results. Next, the recall values measured for each of the chat messages, M-26 to M-50 that had been selected for the experiments. The best produces are computed using four messages from chat. In this case, M-28 yields a recall value of 0.985, while M-29 yields a recall value of 0.988. Using M-32 and M-33, the maximum recall values are computed, and the result is 0.999. These particular communications are used to arrive at an average known result of 0.887. Figure 13 shows a graphic illustration of the computed values.

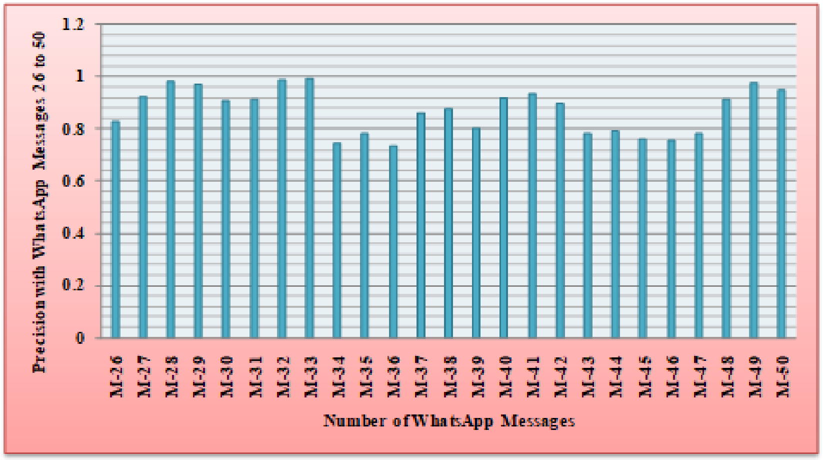

Figure 9. Measured Precisions with 26 to 50 Chat Messages

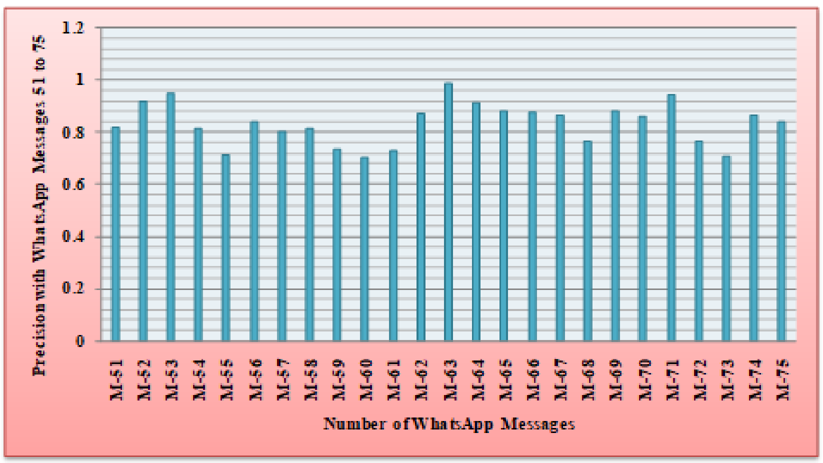

Figure 10. Measured Precisions with 51 to 75 Chat Messages

It was also noted that the method's recall efficiency using these particular chat messages is better than that of the M-1 to M-25 chat messages.

By applying the CNN model, remembering accomplishment from the chat messages from M-51 to M-75 is calculated and assessed. Figure 14 displays the recall evaluation technique's results. These preference was for students' WhatsApp chat messages have an average recall value of 0.853 when measured. Chat message M-63 yields the highest recall value of 0.992. Additionally, the recall amounts of the chat messages from M-76 to M-100 can be seen in Figure 15. As the graph demonstrating the recall values for each message is being analyzed. Because the majority of recall values reached at 0.1 as well as certain are above the threshold, it is seen that the developed sentiment analysis system provides the necessary results with the selected chat messages. The performance of the system totally increased with the increase in calculated values.

7 Cumulative Results

Four sections of the 100 messages in chat dataset were used to conduct tests and determine the outcomes. The majority of scholars trained and tested datasets by employing the generated neural network system by deploying the K-Fold cross validation approach. Rather than employing this method, directly separated

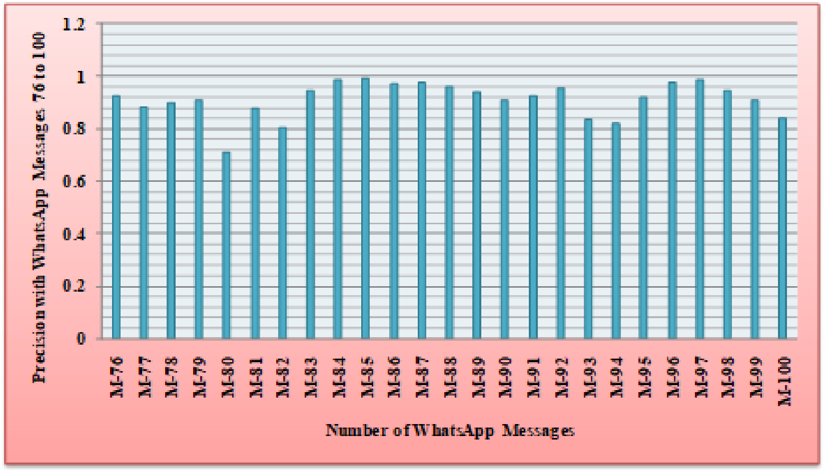

Figure 11. Measured Precisions with 76 to 100 Chat Messages

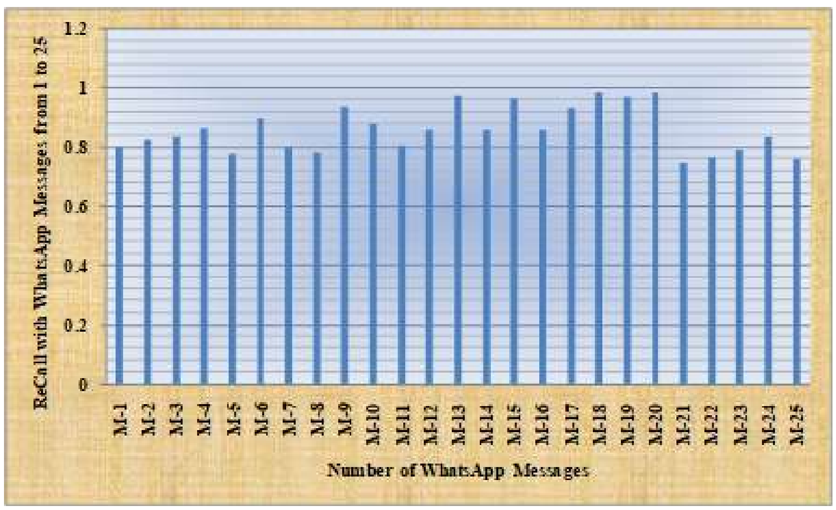

Figure 12. Measured Recall Values with 1 to 25 Chat Messages

the produced datasets into four classes in order to measure the outcomes using four selected assessment techniques—accuracy, precision, recall, and f-score.The performance of the developed CNN model calculated against SA. The total accuracy of 0.874 is calculated using 100 selected at random Sindhi-language chat messages. Likewise measured the precisions of each chat message after the correctness calculation had been done, and the CNN model gave back an average precision of 0.863. Furthermore, the combined recall value of 0.883 is calculated using the designed programming language and proposed CNN model, demonstrating the better accuracy of the constructed sentiment analysis system.

The obtained results proved that the students of the universities are frequently used social media networking websites and share their sentiments with the students, teachers and others. The shared student's sentiments must be analyzed for the improvement of the academic studies and other related activities. The sentiment evaluation performance will also help to monitor the negative activities of the students. In this research only WhatsApp messages are selected but in future the messages of other social media will be selected and investigated.

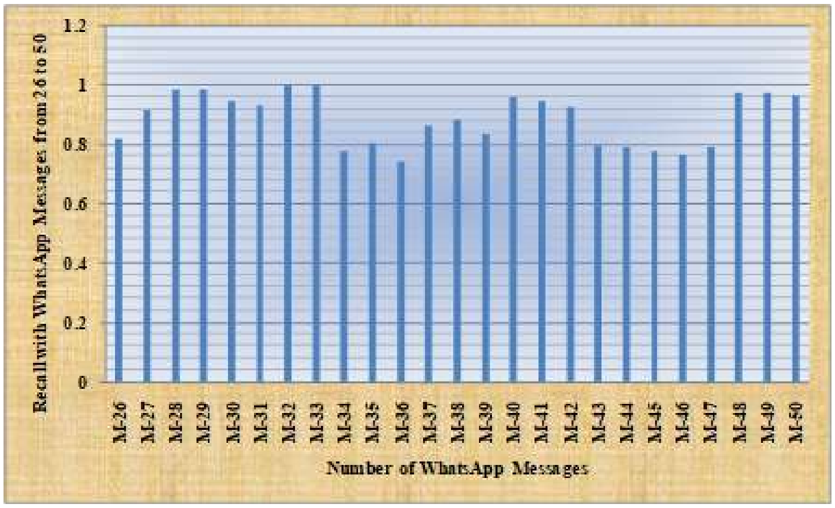

Figure 13. Measured Recall Values with 26 to 50 Chat Messages

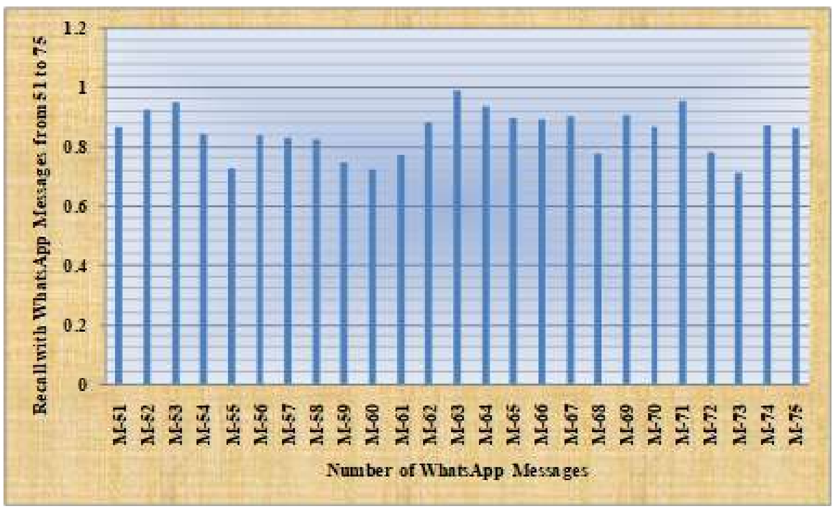

Figure 14. Measured Recall Values with 51 to 75 Chat Messages

8 Conclusion

Using various official WhatsApp communities belonging to undergraduate students, Sindhi text is identified as an object by the methodology employed in this study. Two contributions have been provided by this work: (1) Robust Sentiment Analysis, which infers human sentiment from Sindhi text; and [2] a novel network that examines the interaction between text and affective image regions in multimodal analysis of sentiment. The students' SA results are highest when multiple approaches are utilized. Four categories are created from a subset of the chat messages. The conclusions are calculated individually and presented according to the chat groups. The results of the SA of the students' messages are presented in figures to aid those reading or reviewing in interpreting the stated results. The best possible quality of classification provided by the method, the suggested value is 98.97%. However, the accuracy of the 87% is measured owing to the orthographic difficulties of the Sindhi language. It is obligatory to compare the obtained results with already published work. As this research project is purely based on our own developed datasets and no work is published before. Hence, the outcome of this work is

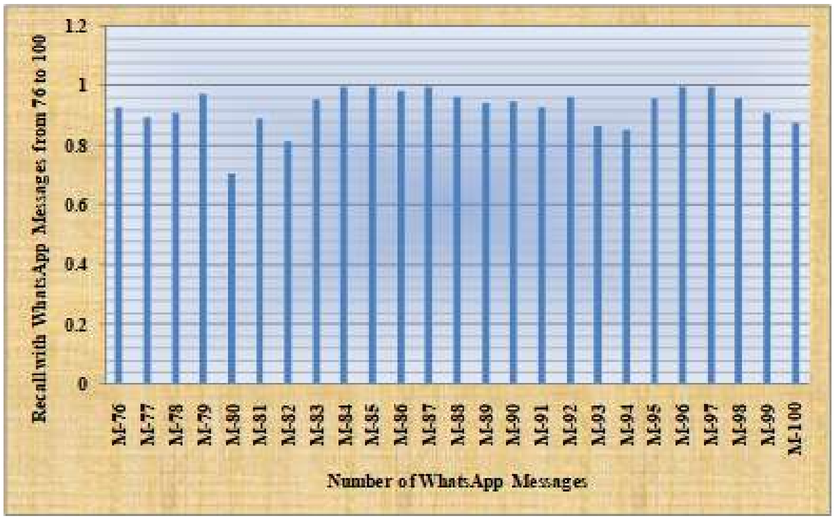

Figure 15. Measured Recall Values with 76 to 100 Chat Messages

not compared. In future, some other techniques will be implemented on same datasets then researchers will compare the results.

9 Conclusion

This study proposed DEAODV reacting routing protocol which is based on a conventional AODV routing protocol. The DEAODV routing protocol focuses on the effective usage of MANET in the disastrous or emergency related situation. A traditional AODV do not considering node energy and frequently link failure issues during the broadcasting of control packets, which causes huge amount of node energy has been drain out during the receiving and transmitting of data packets. For the better performance of the network, DEAODV select best feasible routes based on node energy consumption and shortest distance among the participating nodes. The proposed DEAODV significantly enhance network lifetime by improving packet delivery ratio, reduces End to End Delay, improves throughput, reduces packet loss, reduce normalized routing overheads and reduces the node energy consumption. This study helps researchers to develop new real time applications in future which support first responders in evacuation process in disaster management system. The new developed applications helps to improve network performance in disastrous situation. The proposed DEAODV protocol sets a foundation for numerous future research directions, particularly in enhancing disaster-resilient communication networks. One promising avenue for future work is the integration of more advanced energy optimization techniques, such as adaptive power control mechanisms. By dynamically adjusting transmission power based on network conditions, such protocols could further extend node and network lifetime. Researchers could explore hybrid approaches that incorporate both energy-awareness and additional environmental factors, like signal interference and varying terrain in disaster zones, to create more resilient routing solutions.

Another potential direction lies in the exploration of AI-driven algorithms for route optimization. Machine learning models could be trained to predict node energy depletion rates and adjust routes preemptively to avoid energy-drained nodes, enhancing the network's adaptability in real-time. Additionally, incorporating reinforcement learning could help MANETs autonomously learn optimal routing paths based on previous data patterns, improving routing efficiency over time. This would be especially beneficial in unpredictable disaster scenarios where communication demands and environmental conditions fluctuate rapidly. Furthermore, the DEAODV protocol could be extended to support multi-tier network architectures involving drones or unmanned aerial vehicles

(UAVs) alongside ground-based nodes. UAVs can act as relay points or mobile nodes to cover more extensive areas, particularly in hard-to-reach or heavily damaged locations. Future work could focus on optimizing routing in these multi-layered MANETs, ensuring seamless data relay between aerial and ground nodes for maximum network coverage and resilience. Integrating such flexible architectures with DEAODV may offer critical advantages in complex, large-scale disasters.

Author Contributions

Shahid Ali Mahar: Idea, Methodology, Writing- Original draft preparation **Muhammad Imran Mushtaque**: Supervision **Mashooque Ali Mahar**: Analysis **Javed Ahmed Mahar**: Simulation work **Aurangzeb Magsi**: Software, Validation

Compliance with Ethical Standards

It is declare that all authors don't have any conflict of interest. It is also declare that this article does not contain any studies with human participants or animals performed by any of the authors. Furthermore, informed consent was obtained from all individual participants included in the study.

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