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RESEARCH ARTICLE

Text Mining and Emotion Classification on Monkeypox Twitter Dataset: A Deep Learning-Natural Language Processing (NLP) Approach

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ABSTRACT Emotion classification has become a valuable tool in analyzing text and emotions people express in response to events or crises, particularly on social media and other online platforms. The recent news about monkeypox highlighted various emotions individuals felt during the outbreak. People's opinions and concerns have been very different based on their awareness and understanding of the disease. Although there have been studies on monkeypox, emotion classification related to this virus has not been considered. As a result, this study aims to analyze the emotions individual expressed on social media posts related to the monkeypox disease. Our goal is to provide real-time information and identify critical concerns about the disease. To conduct our analysis, first, we extract and preprocess 800,000 datasets and then use NRCLexicon, a Python library, to predict and measure the emotional significance of each text. Secondly, we develop deep learning models based on Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), Bi-directional LSTM (BiLSTM), and the combination of Convolutional Neural Networks and Long Short-Term Memory (CLSTM) for emotion classification. We use SMOTE (Synthetic Minority Oversampling Technique) and Random Undersampling techniques to address the class imbalance in our training dataset. The results of our study revealed that the CNN model achieved the highest performance with an accuracy of 96%. Overall, emotion classification on the monkeypox dataset can be a powerful tool for improving our understanding of the disease. The findings of this study will help develop effective interventions and improve public health.

INDEX TERMS Monkeypox, emotion detection, deep learning, natural language processing (NLP), sentiment analysis.

I. INTRODUCTION

The recent outbreak of the monkeypox virus has highlighted the importance of understanding how the public perceives and responds to diseases. It's clear that the outbreak caused much anxiety among people in various countries. The World Health Organization (WHO) referred to the situation as a public health emergency on July 23, 2022 [1], and the US Department of Health & Human Services also declared the outbreak a public health emergency on August 4, 2022 [2].

Monkeypox is a rare viral disease that can have significant health impacts on individuals and communities. While much research has focused on developing treatments and vaccines for the disease, there is increasing interest in understanding public perceptions and emotions related to monkeypox. Having a deeper understanding of the psychological effects of this disease may help us to better prepare and assist individuals in controlling their anxiety due to the uncertainty of the situation.

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With the widespread use of social media and the growing availability of online news articles, large amounts of text data can be generated for analysis [3]. Emotion classification is a technique that can be used to analyze text, particularly on social media, to gain insights into how people feel about events or happenings. This process is widely used across various domains, such as psychology, marketing, and political science to analyze people's attitudes. Researchers can identify areas of concern by classifying text data into different emotional categories using deep learning algorithms or machine learning techniques. The information generated during analysis can help public health officials develop targeted approach and effective communication strategies to addressing disease outbreaks.

It is imperative to closely examine emotions when analyzing people's sentiments on a particular matter. In this way, it will be possible to determine their psychological state at a given time. The classification of emotions during a disease outbreak like monkeypox can help identify the emotional distress people experienced during this period. This can help design a psychological support program for individuals impacted. According to the authors in [4] and [5], emotions can be categorized into discrete and dimensional. The concept of discrete emotion refers to the experience of one fundamental emotion like fear, joy, or surprise. In contrast, the concept of dimensional emotion pertains to a person's conception of at least two fundamental emotions such as arousal and valence [6]. The illustration of Plutchik's colored wheel [7], shows that humans have eight primary emotions which are surprise, sadness, disgust, anger, anticipation, joy, trust, and fear.

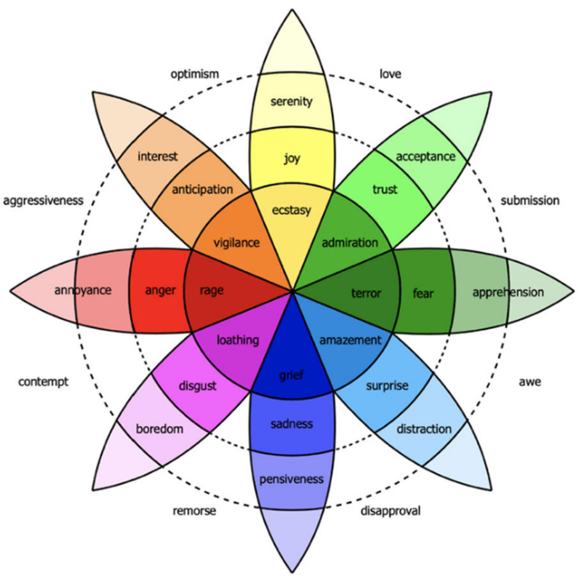

FIGURE 1. Plutchik's colored wheel [7].

In Figure 1 the inner wheel displays the highest level of arousal, while the outer wheel displays the lowest level of arousal, which results in different emotions [6], [7]

The purpose of this study is to conduct emotion classification on monkeypox dataset. This study uses emotion classification techniques to analyze text related to the monkeypox outbreak on Twitter. To extract and preprocess the dataset, we used various natural language processing techniques. To categorize and label the emotions in texts, NRCLexicon [8] was applied which was used to classify the text data into eight categories. For the development of our models, deep learning algorithms such as LSTM, CNN, CNN-LTSM, and BILSTM were utilized. The data was separated into two groups so that the prediction model was trained on 80% of the data and tested on 20% of the data to identify the best model for prediction. The rest of the paper is organized as follows: Section II provides a detailed review of related works. Methods for analyzing data are discussed in Section III. The experimental results are presented in section IV. Section V discusses our contribution and future work, and section VI presents the final discussion.

II. LITERATURE REVIEW

In recent years, social media has emerged as a very powerful tool for communication that makes sharing thoughts and feelings effortless. But it has also created a complex environment where reactions and emotions vary widely. This is why it's critical to understand how people react to real-life events. A growing field of sentiment analysis utilizes social media data to capture public opinion on various events such as political movements, marketing campaigns, natural disasters, health-related events, terrorist activities, and many others [9].

Various studies have conducted sentiment analysis across different domains, particularly in marketing and health-related issues. Many of these studies have shown several methods for analyzing the sentiments and emotions of people during different events. Authors in [10] conducted a study on sentiment analysis with one of the methods. Their study analyzed customers' opinions in a market survey using TextBlob, a natural language processing approach to understand customer opinions and views about the market trends. This study proposed techniques to help decision-makers to take informed decisions about their market strategy. In [11], the authors presented a comprehensive survey of analyzing opinions in tweets. Using lexicon-based approaches and machine learning, this study examines different algorithms for analyzing Twitter data streams, including Naive Bayes, Max Entropy, and Support Vector Machines, as well as their evaluation metrics, and compares these approaches. A survey like that presented by the authors in [11] is the study in [12] which explored different deep-learning approaches to sentiment analysis. The study presented state-of-the-art techniques and tools used to analyze text. Research has shown that analyzing people's feelings about various health issues can help identify potential trends, develop effective interventions, and improve healthcare quality.

The spread of information about some disease outbreaks on Twitter has been examined in various studies. A study conducted by Liang et.al [13] examined how information spread on Twitter as well as identified influential users regarding Ebola posts. In their study, Ebola-related tweets posted globally from March through May 2015 were obtained and analyzed to investigate retweeting patterns. Their result showed that influential users could trigger many tweets and their source of information could be a potential communication strategy for public health promotion. Research such as [14] investigated public opinions related to the swine flu outbreak in 2009. It focused on identifying and analyzing the popularity of trusted information sources such as news outlets and official health agencies. The results of their studies indicate that reputable sources are more popular than untrusted ones.

Authors in [15] analyzed the outbreak of the Zika virus on Twitter after the World Health Organization declared it a global emergency. The analysis revealed five main themes such as the impact of the outbreak on society, responses from the government and the general public, health consequences to pregnancy, ways in which the virus is transmitted, and reported cases. Their result showed that proactive planning and preparedness can help minimize the event of an outbreak. Mansoor et al. [16] presented a global sentiment analysis of tweets related to the Coronavirus. The study examined how people's sentiments in different countries changed over time and explored the impact of the virus on daily life. In their study, tweets related to remote work (WFH) and online learning were extracted, machine learning models such as Long Short-Term Memory (LSTM) and Artificial Neural Networks (ANN) were used to classify the sentiment of tweets and their accuracy was determined.

Mohbey et al [17], examines the sentiment polarities in monkeypox tweets using a hybrid deep learning technique, CNN, and LSTM. This technique was used to determine the accuracy of their model. The authors sought to investigate people's perceptions of monkeypox illnesses to increase awareness of monkeypox infection in the general population. An exploratory analysis of tweets sentiments was conducted by Ng et al. [18] on the current monkeypox outbreaks using an unsupervised machine-learning approach to social media posts. The data extracted was based on tweets related to the monkeypox virus. The study includes topic modeling with a total of 352182 Twitter posts analyzed. Their result shows concerns about safety, stigmatization of minority communities, and a general lack of faith in public institutions.

Sitaula and Shahi [19] compared 13 pre-trained deep-learning models for the detection of the monkeypox virus on a publicly available dataset. Their models were fine-tuned with universal custom layers and evaluated using Precision, Recall, F1-score, and Accuracy. The best-performing models were then combined using a majority voting approach to improve the overall performance. The results surpass the current state-of-the-art methods and suggest that the proposed approach could be useful for mass screening by health practitioners.

Bengesi et al. [26] conducted sentiment analysis on the monkeypox outbreak. The goal of this study was to understand the public's view and prevent misinformation about the disease. In their study, a multilingual Twitter text dataset was analyzed using machine learning and NLP techniques: Vader and textblob, stemming, and lemmatization. Their study presented 56 models with the highest predicting model having 93% accuracy. However, the scope of this study does not extend to emotion classification.

Emotion classification of text data related to an event is an area of study in the field of natural language processing (NLP) that aims to automatically classify human thoughts, views, and emotions expressed in texts related to the happenings. It can be used as a driving force in activism, as it is the heart of everything we do. It encourages participation in any movements and sustained involvement within them. A study conducted by Field et al. [20], adopted natural language processing techniques to analyze emotions conveyed in tweets about the 2020 black lives matter protests. In their study, a few-shot domain adaptation approach was used to measure the different emotions expressed in the tweets following the death of George Floyd in May 2020. Their result showed high levels of expressed anger and disgust overall posts. This work demonstrates how natural language processing techniques can be used to give insight into social movements and methods for extracting text data from social media.

Like the authors in [17], Imran et al. [21] conducted a study to analyze the emotional reactions and sentiments of people from different cultures towards the novel coronavirus and the actions taken by different countries to combat its spread. The authors utilized sentiment analysis and deep learning techniques, using deep long short-term memory LSTM models. These models were trained on the sentiment140 dataset, and their results revealed state-of-the-art accuracy in estimating the sentiment polarity and emotions of individuals. The scope of related articles is summarized in Table 1.

Despite the wealth of research in sentiment analysis, emotion classification on monkeypox data remains unexplored, as shown in Table 1. As a result, our research seeks to bridge the gaps from earlier studies.

1) In our previous work [26], we analyzed the sentiment of the large volumes of text in response to the monkeypox outbreak using machine learning approach. In this study, we will identify and provide a more nuanced understanding of specific emotions expressed by individuals related to the monkeypox outbreak using a deep learning approach.
2) As more content is being created on social media, there is a need to explore techniques for analyzing text and emotion in multilingual content. This will allow analysis in a global context and increase classification accuracy. Unfortunately, there is currently a lack of research on emotion classification in multilingual tweets related to the monkeypox outbreak.
3) There is also a gap in knowledge about the use of emotion analysis to assess the emotional impact caused by the monkeypox outbreak on the public. This study aims to fill that knowledge gap.

TABLE 1. Literature review summary.

Authors	Datasets	Polarity	Emotion	Labelling	Model	Results
Mansoor et al. [16]	165,116 coronavirus tweets on Kaggle, 40,756 online learning tweets, and 41,349 work from home tweets.	Positive Negative Neutral	Fear and Trust	NRCLex for emotion labelling, Vader	LSTM, CNN. Vader, ANN	84.5% accuracy for LSTM and 76% accuracy for ANN
Mohbey et al.[17]	61,379 tweets	Positive Negative Neutral	N/A	N/A	CNN, LSTM, SVM, Naives Bayes, Logistic Regression	CNN-LSTM: Accuracy of 94%
Ng et al. [18]	352,182 tweets	N/A	N/A	N/A	BERT	The model generated five topics about public discourse around monkeypox. 68.9% were related to the topic while 31.1% were from a topic not included in the current results.
Sitaula and Shahi [19]	Public dataset	Positive Negative Neutral	N/A	N/A	MobileNet, Xception, DenseNet, VGG, ResNtet, and EfficientNet	Ensemble model (Xception as M1 and DenseNet-16) achieved an Accuracy of 87.13%.
Field et al. [20]	34.1 M tweets	N/A	6 Emotions of Ekman's taxonomy	N/A	Base TGT, FSL, LIWC and Machine Learning Model	The model shows that +TGT+FSL performs better than other models followed by few-shot learning, machine learning models and then LIWC.
Imran et al. [21]	460,286 tweets (Kaggle), 27,357 tweets, and 1.6 M tweets (Sentiment 140)	Positive Negative Neutral	6 NRC Emotions	NRCLex for emotion labelling	CNN, LSTM	Accuracy of 81.1% for CNN was achieved.
Sv and Ittamalla [22]	556,402 tweets	Positive Negative Neutral	N/A	TextBlob	LDA	Positive: 28.82% Neutral: 48.16% Negative: 23.01%
Çakar and Sengur[23]	COVID-19 real world worry dataset	N/A	8 NRC Emotions	Manual	NB, SVM, KNN, ANN, DT	75.7% accuracy for ANN was achieved.
Kabir and Madria[24]	10,000 COVID-19 tweets	N/A	8 Emotions	Manual	BiLSTM	Accuracy of 0.8951 was achieved.
Shasini and Badugu[25]	10,48576 tweets from (Sentiment 140)	N/A	4 Emotions	N/A	RBA and NB	Accuracy of 88% for NB

Concisely, we seek to provide a picture of how the public responded to the threat of monkeypox. We believe this information might be helpful to improve public health communication.

III. MATERIALS AND METHODS

A. OVERVIEW

Figure 2 illustrates the overall framework of our experiment. The experimental framework begins with data collection from Twitter using Tweepy and the Twitter API. We then preprocessed the data removing retweets, punctuation, hashtags, user tags, numbers, contradictions, non-ASCII characters, URLs, and repeated words from the dataset. Also, Emoji conversion and translation were other preprocessing tasks performed in our study. For emotion labeling, we use NRCLEX, then develop our models using deep learning algorithms such as CNN, LSTM, and BiLSTM. This study has 8 prediction classes as illustrated in the framework and the best performing model was identified.

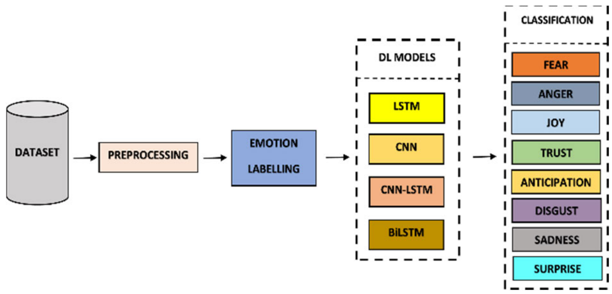

FIGURE 2. Framework overview.

B. DATA COLLECTION

In this study, Twitter APIs and the Tweepy library were used to extract tweets from Twitter. We used Tweepy, a Python package, to access the Twitter API and collect Twitter content. This included tweets, retweets, and timestamps that were posted. To extract all tweets containing the keyword ‘‘monkeypox’’, a Python script was developed where all text that met our criteria was removed and stored in a comma-separated value file (CSV). A total of five features were considered for our extraction: text, timestamps, authors, sources, and languages. The non-English tweets were translated using the Google Translate API. Between July 2022 and December 2022, we collected over 800,000 tweets; however, after preprocessing, we were left with 227347 unique tweets. We had approximately 103 languages in total in our dataset and the top 5 are shown in Table 2.

TABLE 2. Top 5 languages distribution.

Language	Count
English (en)	138,358
Portuguese (pt)	5,208
Spanish (es)	4,168
French (fr)	3,993
Turkish (tr)	1,078

C. DATA PREPROCESSING

Data cleaning is an important step for any data analysis task. Our goal was to remove all unnecessary content from the dataset to leave a suitable dataset for model training and inference. We eliminated empty tweets, all Retweets (RT) which were reposted tweets and User tags which were Twitter usernames. In addition, hashtags, numerals, repeated words, stopwords, and punctuation were removed because they do not contribute to model training. Emojis were converted to their proportionate text using an Emoji Python package and all contraction words were dilated to form the original words. Preprocessing the dataset reduces computing costs and accelerates the training and prediction process.

D. EMOTION LABELLING

NRCLex or NRCLexicon is a python package that measures emotional significance on text. It uses NLTK library's WordNet synonym sets and an affect dictionary of approximately 27,000 words based on the National Research Council Canada (NRC) affect lexicon [8]. The package measures ten categories of emotion, that is two more than those suggested by Plutchik [22]; those two are positive and negative sentiments. We removed examples of these two categories from our dataset to stick with the Plutchik-8 emotions [4] as those categories reflect the sentiment of the text instead of the emotion which is a finer level of sentiment. In our previous work [26], we performed the sentiment analysis on the Monkeypox disease. Our dataset now consists of 153408 tweets which we divided into 80% for training (122726 instances) and 20% for test (30682 instances). Algorithm 1 illustrates the emotion labelling algorithm.

Algorithm 1 LABELING STEPS

start :
Input: Unlabeled Dateframe: dfu
Output: Labeled Dateframe: dfl
For each row in dfu:
  if row [‘language’]not in[“English",“Undefined"]:
    row[‘Translate’]=Google translate(row[‘text’])
  else
    row[‘Translate’]=row‘[text’]
  row [‘Emotion’]=NRCLex(row’[Translate’])
end:

Fear, anger, trust, joy, anticipation, disgust, surprise, sadness were the types of emotion detected in our dataset. As shown in Table 3 Fear was the most prevalent emotion with 67.8 % of all emotions available while joy was the least expressed emotion with approximately 0.03%.

TABLE 3. Emotion distribution.

Emotion	Count
fear	104029
trust	31445
anger	6370
anticipation	5515
surprise	4618
disgust	976
sadness	405
joy	50

E. DATA BALANCING

Classification using class-imbalanced data is generally biased in favor of the majority class [27], [28]. A dataset is imbalanced if one subset (class) of the data has dominance over other subset (classes) of the data [29]. Our dataset is imbalanced with fear emotion representing more than half of the data. This can affect the classifier's ability to detect accurately all the emotions present in the dataset if not addressed. Techniques dealing with imbalance dataset are generally grouped into two categories: algorithm level methods and data level methods [30]. Data level approach includes under sampling and oversampling of the training dataset [31], [32]. We experimented with these two techniques.

1) OVERSAMPLING WITH SMOTE

We applied the Synthetic Minority Oversampling Technique (SMOTE) [33] method to create and add synthetic minority class examples to the training dataset until a more balanced class distribution was obtained. Imblearn python library implementation was used in this technique. Our training dataset consists of 122726 instances (80% of the dataset) with fear (majority class) claiming 83223 instances, i.e., 67.8 % of the training data. The goal of the oversampling was to increase the number of examples of the minority classes (anger, trust, joy, disgust, anticipation, surprise, sadness) so that each class has 83223 examples in the dataset, thus balancing the data. SMOTE works by selecting a random example from the minority class first and applied the K (usually K=5) nearest neighbors' algorithm to generate a synthetic example which is added to the dataset. Figure 3 shows the SMOTE process.

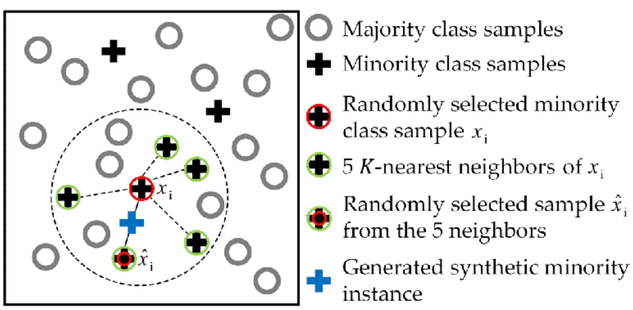

FIGURE 3. SMOTE algorithm [34].

At the end of our oversampling process, we obtained 665,784 examples (83223 × 8 examples) in the new training dataset. Figure 4 shows the distribution of the classes in the training dataset after the application of the oversampling technique.

2) SMOTE COMBINED WITH RANDOM UNDERSAMPLING

To experiment with the second technique, we created a new training dataset by applying random undersampling [35] to the dataset obtained after the oversampling with SMOTE. Various undersampling methods such as Condensed Nearest Neighbor, Edited Nearest Neighbor, Neighborhood Cleaning, Tomek Links and One-sided selection have been proposed [36]. Due to computation resources limitation, we leverage the basic random undersampling technique shown in figure 5 as implemented by the RandomUnderSampler in the Imblearn python library [37]. Our goal was to reduce the augmented training dataset to a size close to its original size (122726 examples) while keeping the balance in the distribution of the emotions. We divided the number of examples in the original training dataset by the number of emotions (classes) to obtain the desired proportion for each emotion, i.e., 122726 / 8 = 15341 (approximately).

In this approach, instances of the target classes were randomly removed until a more balanced class distribution was achieved. Figure 6 shows the new distribution of the training dataset after this step.

F. DEEP LEARNING MODELS

We built four deep learning models: Long Short-Term Memory (LSTM), One Dimensional Convolutional Neural Networks (1DCNN), CNN-LSTM, and Bidirectional LSTM (BiLSTM). Hyperparameter tuning was performed on our models to determine the most appropriate parameters using Sklearn RandomizedSearchCV class. A maximum feature size of 2000, and an embedding dimension of 200 were used for all the models.

1) LONG SHORT-TERM MEMORY (LSTM)

LSTM is an RNN model designed with the capability to overcome long-term dependencies challenge developed by Hochreiter and Schmidhuber [39] in 1997. As figure 7 shows, our LSTM model included an embedding layer with a dimension of 128, an input length of 74, and a vocabulary size of 2000. We added four LSTM layers using the ReLU activation function with dropouts between them and with only one dense layer after flattening of LSTM layer.

The cells that compose LSTM layers use a gate mechanism to regulate the memorizing process. Information can be stored, written, or read by using gates that open and close throughout the layer [40]. As part of the cell, there are gates such as:

Input gate

This gate considers the relevant features that can be added to the current step and decides what can be added.

$$i_t = \sigma\left(W_i X_t + U_i h_{t-1}\, \mathcal{C}\, b_i\right) \tag{1}$$

Forget gate.

This gate decides whether to keep the feature from the previous timestamp or discard the information.

$$f_t = \sigma\left(W_f X_t + U_f h_{t-1}\, \mathcal{C}\, b_f\right) \tag{2}$$

Output gate

This gate determines what information should be passed on to the next state. This information is made up of previous inputs (the current state and the previous hidden state) which are fed into the sigmoid function, which results in a new cell

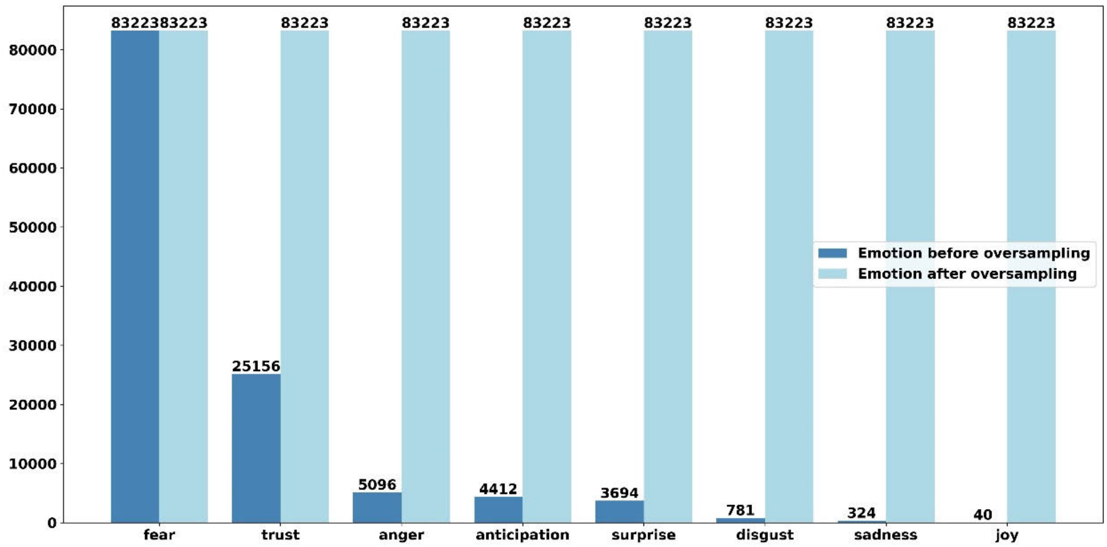

FIGURE 4. Emotion distribution in the training dataset after oversampling.

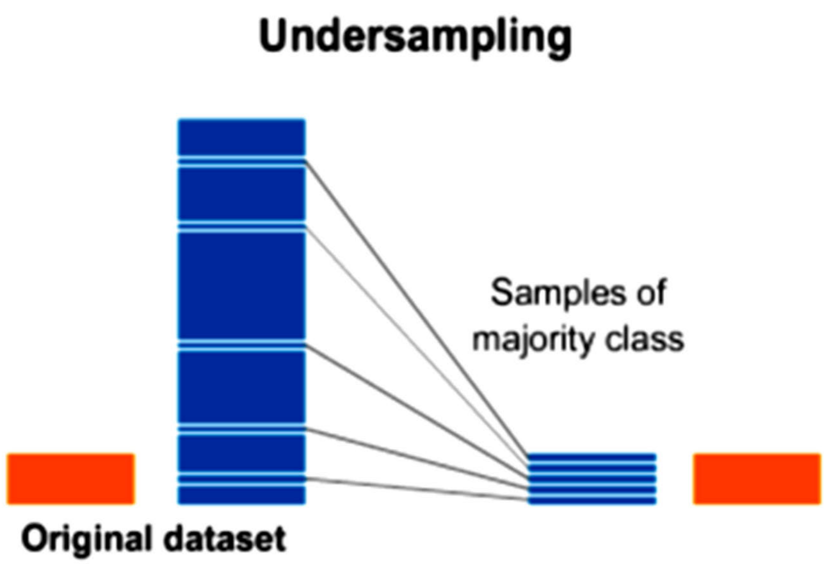

FIGURE 5. Random undersampling [38].

state which is passed through the tanh function.

$$\boldsymbol{o_t = \sigma \left(W_o X_t \,\mathcal{C}\, U_o h_{t-1} \,\mathcal{C}\, b_o\right)} \tag{3}$$

$$\boldsymbol{C_t^{\prime} = \sigma_1 \left(W_c X_c \,\mathcal{C}\, U_c X_{t-1} \,\mathcal{C}\, b_c\right)} \tag{4}$$

$$C_t = f_t C_{t-1} + i_t C_t^{\prime} \tag{5}$$

$$h_t = o_t \sigma_1 \left(C_t\right) \tag{6}$$

The following are represented in Equation 1-6:

$\boldsymbol{\sigma}$1: Tanh Activation function
$\boldsymbol{\sigma}$: Sigmoid Activation function
W: Weight related to hidden state
U: Weight related to input state
ht: Hidden state
Ct: Cell state
Ot: Output gate
ft: forget gate.
it: input gate

2) ONE-DIMENSIONAL CONVOLUTIONAL NEURAL NETWORK (1DCNN)

1DCNN was another deep learning algorithm we implemented; as known, transformation and extraction of features mainly depend on kernel convolution. Convolutional Neural Networks (CNN) have proved their superior performance in image, speech, or audio signal classification. For inputs having more than one dimension such as image, two-dimensional CNNs (2DCNN) are the gold standard [41]. For text processing, 1DCNNs are preferred. CNN has three main

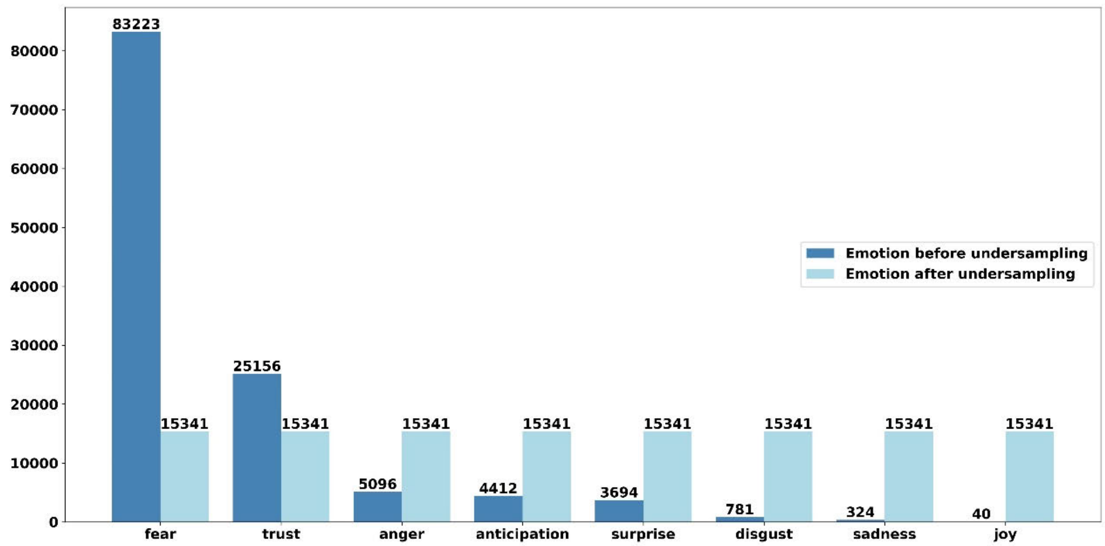

FIGURE 6. Emotion distribution in the training dataset after undersampling.

```
Layer (type)                 Output Shape              Param #
=================================================================
embedding (Embedding)        (None, 56, 200)           400000

lstm (LSTM)                  (None, 56, 256)           467968

dropout (Dropout)            (None, 56, 256)           0

lstm_1 (LSTM)                (None, 128)               197120

dropout_1 (Dropout)          (None, 128)               0

dense (Dense)                (None, 250)               32250

flatten (Flatten)            (None, 250)               0

dense_1 (Dense)              (None, 8)                 2008

=================================================================
Total params: 1,099,346
Trainable params: 1,099,346
Non-trainable params: 0
_________________________________________________________________
```

FIGURE 7. LSTM architecture.

components: the convolutional layer, the pooling layer, and the fully connected layer [42]. The convolutional layer is the central piece of CNN where most of the computation happens. The pooling layer is a downsampling layer which reduces the number of parameters in the input. The fully connected performs the classification by applying weights to the feature inputs of previous layers to predict the final probabilities for each class. In our case, we applied one embedding layer, two of one-dimensional of the convolution layer (Conv1D), two one-dimensional MaxPooling (MaxPool1D), one flattens layer, and four dense layers. Figure 7 shows our architecture for IDCNN.

3) CNN-LSTM

We used a hybrid model that combines the techniques of convolutional neural networks (CNNs) and long-short term memories (LSTMs) [43]. This model implements two layers: a convolution layer and a pooling layer with a dropout between them. The output of the convolution layer and the pooling layer is fed into the LSTM layer followed by the dense layer, which provides the final output. Figure 9 shows our architecture for CNN-LSTM.

4) BIDIRECTIONAL -LSTM (BILSTM)

To improve the existing LSTM, which is a one-directional RNN, a bidirectional LSTM was developed. The algorithm uses two layers of LSTMs, one of which takes the input in a forward direction (one from past to future), and the other of which takes the input in a backward direction (future to past), respectively [44]. With this kind of architecture of RNN, there is an increase in the amount of information available to the network. Thus, the algorithm has access to more context That is, it can recognize what words immediately follow a word in a sentence or what words immediately precede it [44].

The algorithm uses the same LSTM of the gating mechanism as the previous one but in two directions. Sequential forward propagation of BiLSTM is similar to that of LSTM illustrated in equations 1-6, but backward propagation differs by timestamp in the hidden state as shown in equation 7-9 where time is incremented by one [45]. Figure 8 shows our architecture for BiLSTM.

$$\boldsymbol{i_t} = \sigma\left(\boldsymbol{W_i X_t} + \boldsymbol{U_i h_{tC1}} + \boldsymbol{b_i}\right) \tag{7}$$

$$\boldsymbol{f_t} = \sigma\left(\boldsymbol{W_f X_t} + \boldsymbol{U_f h_{tC1}} + \boldsymbol{b_f}\right) \tag{8}$$

$$\boldsymbol{o_t} = \sigma\left(\boldsymbol{W_o X_t} + \boldsymbol{U_o h_{tC1}} + \boldsymbol{b_o}\right) \tag{9}$$

IV. RESULTS

In this section, we present the results of experiments using four deep learning algorithms for classification. As a measure of our model's performance, we used accuracy, precision, recall, and F1 score, which were computed mathematically

Layer (type)	Output Shape	Param #
embedding_16 (Embedding)	(None, 56, 200)	4000000
dropout_78 (Dropout)	(None, 56, 200)	0
conv1d_48 (Conv1D)	(None, 56, 256)	153856
max_pooling1d_48 (MaxPooling1D)	(None, 28, 256)	0
dropout_79 (Dropout)	(None, 28, 256)	0
conv1d_49 (Conv1D)	(None, 28, 128)	98432
max_pooling1d_49 (MaxPooling1D)	(None, 14, 128)	0
dropout_80 (Dropout)	(None, 14, 128)	0
conv1d_50 (Conv1D)	(None, 14, 128)	49280
max_pooling1d_50 (MaxPooling1D)	(None, 7, 128)	0
dropout_81 (Dropout)	(None, 7, 128)	0
flatten_16 (Flatten)	(None, 896)	0
dense_64 (Dense)	(None, 256)	229632
dropout_82 (Dropout)	(None, 256)	0
dense_65 (Dense)	(None, 128)	32896
dropout_83 (Dropout)	(None, 128)	0
dense_66 (Dense)	(None, 64)	8256
dense_67 (Dense)	(None, 8)	520

Total params: 4,572,872
Trainable params: 4,572,872
Non-trainable params: 0

FIGURE 8. IDCNN architecture.

Layer (type)	Output Shape	Param #
embedding_2 (Embedding)	(None, 56, 200)	4000000
bidirectional (Bidirectional)	(None, 56, 128)	135680
bidirectional_1 (Bidirectional)	(None, 128)	98816
dropout_7 (Dropout)	(None, 128)	0
flatten_2 (Flatten)	(None, 128)	0
dense_4 (Dense)	(None, 250)	32250
dense_5 (Dense)	(None, 8)	2008

Total params: 4,268,754
Trainable params: 4,268,754
Non-trainable params: 0

FIGURE 9. BiLSTM architecture.

by the formula shown in equations 10-12 [46].

$$Accuracy = \frac{TP + TN}{TP + TP + FP + FN} \tag{10}$$

$$Precision = \frac{TP}{TP + FP} \tag{11}$$

$$Recall = \frac{TP}{TP + FN} \tag{12}$$

$$F1Score = \frac{2\ X\ Recall\ X\ Precision}{Recall + Precision} \tag{13}$$

Layer (type)	Output Shape	Param #
embedding_17 (Embedding)	(None, 56, 200)	4000000
dropout_84 (Dropout)	(None, 56, 200)	0
conv1d_51 (Conv1D)	(None, 56, 256)	153856
max_pooling1d_51 (MaxPooling1D)	(None, 56, 256)	0
dropout_85 (Dropout)	(None, 56, 256)	0
batch_normalization (BatchNormalization)	(None, 56, 256)	1024
conv1d_52 (Conv1D)	(None, 56, 128)	98432
max_pooling1d_52 (MaxPooling1D)	(None, 56, 128)	0
dropout_86 (Dropout)	(None, 56, 128)	0
batch_normalization_1 (BatchNormalization)	(None, 56, 128)	512
lstm (LSTM)	(None, 56, 64)	49408
lstm_1 (LSTM)	(None, 32)	12416
dropout_87 (Dropout)	(None, 32)	0
flatten_17 (Flatten)	(None, 32)	0
dense_68 (Dense)	(None, 250)	8250
dropout_88 (Dropout)	(None, 250)	0
dense_69 (Dense)	(None, 8)	2008

Total params: 4,325,906
Trainable params: 4,325,138
Non-trainable params: 768

FIGURE 10. CNN-LSTM architecture.

The True Positives (TP) are those values that were accurately predicted as positives, and the True Negatives (TN) are those values that were accurately predicted as negatives. The False Positives (FP) are the values that were inaccurately classified as positives, and the False Negatives (FN) are the values that were inaccurately classified as negatives.

The experiments were conducted on Google Colaboratory Notebook. In our experiment setting, we use two training datasets (one with 665864 examples and the other one with 115056 examples). A total of 80 runs (2 training datasets x 4 models x 10 runs) were performed after the several initial runs for the hyperparameters tuning. For each training dataset, and for each model we performed 10 runs and the results for the performance metrics were averaged. Figure 11, Tables 4 and 5 summarize the results.

The results suggest that the models generally have similar performance. However, CNN outperforms the other models with an accuracy of 96% when trained with more data. LSTM was the least performant model with an accuracy of 94%. The results also showed that the data balancing techniques (oversampling and undersampling) can be very equivalent when the combination of oversampling and undersampling is carefully done.

V. DISCUSSION

This study utilized a natural language processing and deep learning approach to analyze a large volume of text data from social media tweets on the monkeypox outbreak. Emotion classification techniques used in this study provide a better

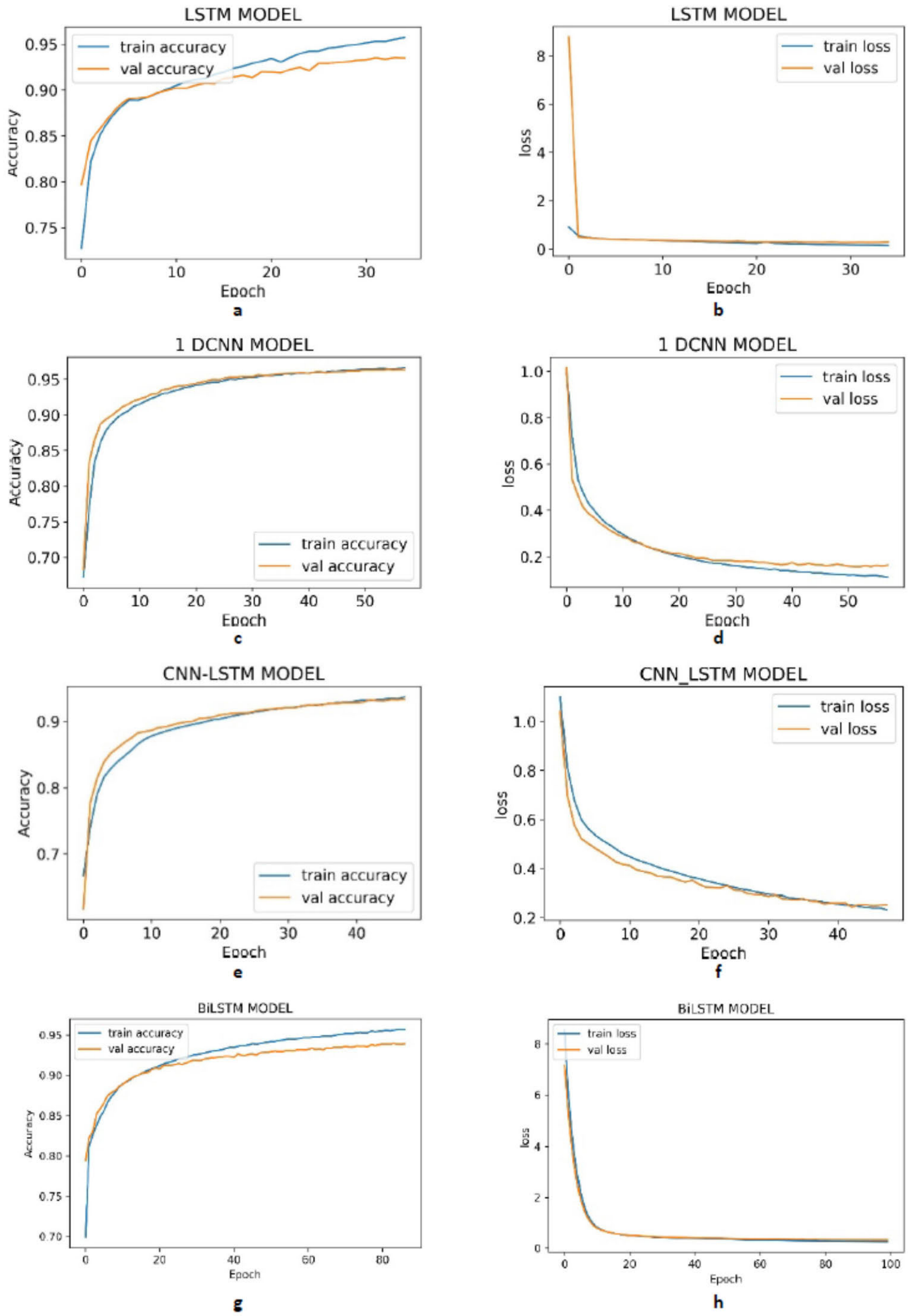

FIGURE 11. **Accuracy and loss for each model during training and test.**

perception of the public's concern and awareness about the disease.

The findings of this study identified fear as the dominant emotion expressed accounting for more than half of the emotion observed in the dataset. Fear and safety concerns are expected, especially when the world has just recovered from the COVID-19 pandemic commotion. The sporadic spread of monkeypox, accompanied by the declaration by the World Health Organization, that the disease might transform into another pandemic, may have been the reason behind a high level of emotional intensity.

Although the monkeypox virus is not easily spread as COVID-19 pandemic, it still presents some threat due to global connectedness. As a result, effective communication

TABLE 4. Model'S performance with oversampling training dataset.

Metrics	Accuracy	Precision	Recall	F1 Score
1DCNN	96.20	96.21	96.24	96.24
LSTM	94.76	94.88	94.90	94.76
C-LSTM	95.22	95.15	95.22	95.16
BiLSTM	95.09	95.24	95.09	95.05

TABLE 5. Model'S performance with undersampling training dataset.

Metrics	Accuracy	Precision	Recall	F1 Score
1DCNN	95.36	95.30	95.36	95.29
LSTM	94.32	94.19	94.32	94.23
C-LSTM	95.12	95.02	95.12	95.07
BiLSTM	95.39	95.33	95.39	95.37

and surveillance are needed to prevent public panic. This paper contributes to existing knowledge as follows:

1) While existing research on monkeypox focuses on the epidemiology of the disease, this study explores another perspective. We examined the emotional impact of the disease outbreak on the public. These aspects are often overlooked in research according to table 1. None of the previous studies in [17], [18], [19], and [26] considered emotion classification. We believe this study can contribute to public health data and the growing need for more holistic approaches to address disease outbreaks.
2) The emotion classification conducted in this study was based on multilingual content that was not considered in many previous works [17], [18], [19], [26]. We analyzed over 103 language tweets to capture a wide range of emotions among different people, since emotions and expressions vary across cultures and languages. It also helps avoid bias towards a specific language in classification.
3) In this study, we developed and evaluated four deep learning models based on the Accuracy, F1 Score, Precision, and Recall metrics. All our models classified emotions accurately with an accuracy rate of 95%. CNN achieved the highest accuracy level with a 96% accuracy rate.

Emotional classification has proven useful in measuring the psychological impact of any diseases outbreak on individuals and communities. This study generates data-driven insights that enhance and complement existing research findings, guiding future research and interventions.

VI. CONCLUSION

In Natural language processing, emotion classification of text data related to disease outbreak is increasingly important. A better understanding of people's emotions is provided by this work. Our study classified monkeypox tweets based on emotion. We extracted over 800,000 tweets from Twitter across 103 languages. The dataset was preprocessed, labeled using NRCLex, and divided into 80% training and 20% test data. Eight emotions were identified in our classification. Fear accounted for 67.8% of all emotions, while joy accounted for approximately 0.03%.

SMOTE Oversampling as well as Random Undersampling techniques were used to deal with the data imbalance in the dataset in order to achieve accuracy and avoid bias in the model. Moreover, we developed four suitable models for emotion classification based on deep learning architecture, including 1DCNN, LSTM, C-LSTM and BiLSTM. Based on our evaluation, we found that our models can predict emotions with 95-96% accuracy and outperformed other systems [15], [25], [47].

In the future, we will analyze the temporal trends of emotion during the monkeypox outbreak. Weekly and monthly evolution of emotion will be considered. We will also investigate the relationship between the languages and the emotion present in the tweets. Emotion co-occurrence will also be analyzed. We plan to use our models for transfer learning to classify emotion across several diseases such as Ebola, Zika, and COVID-19.

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