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Sentiment Analysis in Social Media Data for Depression Detection System

[1]N.H.P. Ravi Supunya, [2]Bhagyanie Chathurika, [3]Subasinghe B.N.W, [4]Aththanayake K.A, [5]Waidyarathna W.D.M.U.P, [6]G.A Asahara

[1]Supervisor, Faculty of Computing, Sri Lanka Institute of Information and Technology, Sri Lanka
[2]Co-Supervisor, Faculty of Computing, Sri Lanka Institute of Information and Technology, Sri Lanka
[3,4,5,6]Undergraduate Student, Faculty of Computing, Sri Lanka Institute of Information and Technology, Sri Lanka
Authors E-mail: [1]ravi.s@sliit.lk, [2]bhagyanie.c@sliit.lk, [3]bniboja@gmail.com, [4]kalpani.arunamali98@gmail.com, [5]udithwaidy99@gmail.com, [6]abeethaasahara@gmail.com

***Abstract* - This research introduces depression as a prevalent mental health condition affecting millions of people worldwide. A sentiment analysis framework is developed for Facebook to detect signs of depression within user posts. The system uses NLP (natural language processing) and machine learning algorithms (CNN) to analyze sentiment and classify posts as positive, neutral, or negative. The framework integrates into Facebook's infrastructure, enhancing accuracy and efficiency. It incorporates user-specific contextual information and performs comparative analyses against existing methods and clinical evaluations. The results show the system effectively identifies posts indicative of depressive sentiments with high accuracy and sensitivity. The sentiment analysis framework can be adapted and implemented in various social media platforms, facilitating proactive mental health interventions, and supporting individuals in need. Integrating the system into digital health solutions can contribute to a more comprehensive approach to mental health care, reaching a wider population and providing timely support.**

Keywords: Sentiment Analysis, Social Media, Depression, Detection System.

I. INTRODUCTION

In today's digital age, social media platforms have become powerful mediums for individuals to express their thoughts, feelings, and experiences. The widespread adoption of social media has opened up new avenues for researchers and scientists to tap into this vast repository of data and gain valuable insights into various aspects of human behavior, including mental health[1]. One area of particular interest within this field is sentiment analysis, which involves extracting and analyzing emotions, opinions, and attitudes expressed in social media data. Depression, a pervasive mental health condition impacting millions of people globally, has gained increasing attention in recent years[2]. The ability to detect signs of depression from social media data offers a unique opportunity to provide early intervention and support to individuals who may be silently struggling. This research focuses on developing a Depression Detection System specifically tailored for Facebook, a prominent and widely-used social media platform[5]. To achieve this goal, we employ a comprehensive approach to sentiment analysis, utilizing four distinct methods to capture emotional indicators and behavioral patterns associated with depression. The methods employed in this research include:

1.1 Identify Facial Expressions

By analyzing facial expressions captured in profile pictures and shared photos on Facebook, we can gain insights into users' emotional states. Facial expressions have long been recognized as potent indicators of human emotions, offering valuable cues for understanding an individual's mental well-being [8].

1.2 Identify Color, Hashtag and Caption

Combining color, hashtags, and captions: This method involves analyzing various elements of Facebook posts, such as color schemes, hashtags, and captions. These elements contribute to the emotional tone and context of the shared content, providing crucial clues for sentiment analysis and identifying potential signs of depression [20].

1.3 Identify Comments with emojis.

Emojis, stickers, and comments: We explore the sentiment expressed through emojis, stickers, and comments on Facebook. Analyzing the language and emotional content of these elements allows us to gain further insights into users' emotional states and potential indications of depression[21].

II. LITERATURE SURVEY

A 2013 study by De Choudhury, and M., Gamon explores the potential of using social media data, specifically from Facebook, to predict depression. Through the application of linguistic and psychosocial characteristics, the study identifies signs of depression. The findings of this research highlight the significance of social media as a valuable source of data for mental health detection and monitoring.

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The specific technologies employed in their research include Natural Language Processing (NLP), Linguistic and Psychosocial Feature Extraction, Machine Learning and Statistical Analysis. By combining these technologies and techniques, De Choudhury, Gamon, Counts, and Horvitz (2013) were able to develop a framework for predicting depression using social media data. This research has helped to identify people with depression, prevent worsening of mental health conditions, and intervene to promote timely access to appropriate treatment [1].

The paper [2] introduces a proposed model for detecting depression in individuals using data analytics. The data utilized for the study is gathered from the posts of users on two widely used social media platforms, namely Twitter and Facebook. Machine learning techniques are employed to process the collected data obtained from users of social networking sites (SNS). Natural Language Processing (NLP) is applied, and the data is classified using Support Vector Machine (SVM) and Naïve Bayes algorithms. This approach aims to detect depression potentially in a more convenient and efficient manner.

A 2018 study focused on predicting depression using language-based emotion dynamics extracted from Facebook and Twitter status updates. This research was conducted by Cohan, A., & Young. They used sentiment analysis techniques and analyzed longitudinal patterns of language use to identify depressed individuals at risk of depression. Some of the weaknesses of this study are -: The paper does not provide detailed information about the demographics and characteristics of the sample population. This lack of information raises concerns about the representativeness of the sample and the potential bias in the results, while natural language processing techniques were used to analyze the textual content, it is important to note that the interpretation of language and emotions is complex.

However, this research has achieved high results. The specific technologies and techniques utilized in their research include Linguistic Feature Extraction, Natural Language Processing (NLP), Machine Learning and Longitudinal Data Analysis.[4] The research conducted by Ghiassi, Skinner, Zimbra, and Zimbra focuses on sentiment analysis of Twitter brand data using a hybrid system that combines N-gram analysis and dynamic artificial neural networks. The study was published in the journal "Expert Systems with Applications”. In their research, the researchers aimed to develop an effective method for analyzing sentiment expressed towards brands on Twitter. Sentiment analysis, also known as opinion mining, involves extracting subjective information, attitudes, and opinions from text data.

The specific techniques employed in this study include Researchers had used N-gram analysis to capture and analyze word or phrase patterns in Twitter brand data. In this research, dynamic artificial neural networks were used as a machine learning approach to psychoanalysis. ANNs can learn and adapt from input-output examples, allowing them to classify and predict sentiment based on learned patterns. The study has contributed to the field of sentiment analysis by proposing a hybrid approach that leverages both linguistic patterns and machine learning methods to analyze sentiment toward brands on Twitter.[3] The objective of the paper [5] is to use natural language processing techniques to analyze sentiment with a particular focus on depression using Twitter feeds. This testing method classifies each tweet as neutral or negative, thereby identifying depressive trends. Support Vector Machine (SVM) and NaiveBayes classifier is employed for the class prediction process. The study presents the results using key classification metrics such as F1-score, accuracy, and a confusion matrix. The research [6] has proposed a multimedia dictionary learning solution to detect depression by analyzing social media data. Here, a combination of linguistic and visual features extracted from social media posts has been used to identify signs of depression. The proposed multimodal dictionary learning solution has been evaluated using realworld social media data and has shown good performance in depression detection results. The objective of this study [7] was to develop an effective method for detecting depression by combining sentiment lexicons and content-based features. Researchers have focused on using textual data, such as social media posts or online forum discussions, to detect signs of depression. They have worked to improve the accuracy and reliability of depression detection algorithms.

III. PROBLEM DEFINITION

Depression is a widespread mental health concern, necessitating early identification for effective intervention and support. Leveraging the wealth of data available on social media platforms, this project aims to address the challenge of detecting signs of depression through sentiment analysis. The central objective is to develop a sentiment analysis system that can categorize social media content into emotional states, with a specific focus on recognizing potential indicators of depression. This system will integrate machine learning and natural language processing techniques to enhance its accuracy, while also adhering to ethical guidelines and respecting user privacy. Collaboration with mental health professionals will ensure the system's accuracy and its capacity to facilitate early intervention. The expected outcomes include a reliable sentiment analysis model, valuable insights into users' emotional well-being, and a tool to aid in identifying individuals who may benefit from mental health support. By tackling this problem, we contribute to the emerging field of digital mental health and offer a proactive approach to mental health care.

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IV. METHODOLOGY

4.1 Data Preparing

During the data preparation phase, the first step is to load the necessary data. This includes collecting or loading images for identifying facial expressions for sentiment analysis. The facial expression analysis requires the collection or loading of images, while the sentiment analysis involves collecting or loading images such as users profile pictures and images. After loading the data, the next step is categorizing.

For identifying facial expressions, images are labeled based on the emotion state or sentiment associated with the expressions present in the images. This labeling process helps to establish ground truth for training and evaluating the sentiment analysis system. To ensure appropriate model training and evaluation, the dataset then formats images into appropriate sizes or pixels. During the data preparation phase, the first step is to load the necessary data.

This includes collecting or loading images for color analysis and hashtags/captions for sentiment analysis. The color analysis requires the collection or loading of images, while the sentiment analysis involves collecting or loading texts such as hashtags and captions. After loading the data, the next step is labeling. For color analysis, images are labeled based on the emotion state or sentiment associated with the colors present in the images. Hashtags and captions, on the other hand, are labeled based on the emotion state or sentiment conveyed by their content. This labeling process helps to establish ground truth for training and evaluating the sentiment analysis system.

To ensure appropriate model training and evaluation, the dataset is then split into training and testing sets. This splitting is performed separately for images and texts. The training set is used to train the model, while the testing set is used to evaluate its performance.

During the data preparation phase, the first step is to load the necessary data. This includes collecting or loading images or visual elements for identifying emojis, stickers and comments for sentiment analysis. User General Content analysis requires the collection or loading of images or visual elements, while the sentiment analysis involves collecting or loading texts such as comments. After loading the data, the next step is labeling.

For User General Content analysis, images or visual elements are labeled based on the emotion. Comments, on the other hand, are labeled based on the emotion state or sentiment conveyed by their content. This labeling process helps to establish ground truth for training and evaluating the sentiment analysis system.

4.2 Data Preprocessing

The first technique applied is normalization, which is achieved by setting the rescale parameter to normalize pixel values between 0 and 1. Another important preprocessing technique is data augmentation, such as rotation, zooming, and flipping. Data augmentation helps improve the model's generalization ability and reduces overfitting. The images are resized to a target size of (48, 48) pixels using the target size parameter. Furthermore, the color mode is set to grayscale, indicating that the images are converted to grayscale format. The labels for each image are encoded using one-hot encoding, One-hot encoding converts the categorical labels (emotions) into a binary vector representation.

Moving on to data preprocessing, the hashtag and caption data are fitted in the dataset, preparing them for sentiment analysis. Sentiment analysis is conducted on the captions and hashtags to determine the sentiment or emotion conveyed by the content. To facilitate further analysis, the captions are then converted into sequences or numerical representations. In terms of color analysis, the photos are resized to a standard scale suitable for analysis. This step ensures that the input data is consistent.

Additionally, the photos are converted to a common color space, such as RGB (Red, Green, Blue), which is widely used for image processing and analysis. Furthermore, the pixel values of the photos are normalized within a given range to ensure consistency and comparability.

Text Preprocessing:

Clean the comment data by removing special characters, URLs, and irrelevant symbols. Convert the text to lowercase for consistency. Tokenize the comments into individual words or phrases. Remove stop words (commonly used words without much sentiment) from the text.

Emoji and Sticker Processing:

Identify and extract emojis and stickers from the comments. Assign sentiment values or labels to the emojis and stickers based on their emotional associations.

Feature Extraction:

Convert the preprocessed text into numerical representations, such as bag-of-words, TF-IDF, or word embeddings. Incorporate the extracted emojis and stickers as additional features in the data representation.

4.3 Components

In this research, the focus is on utilizing three components for sentiment analysis in the context of depression detection:

- Identify Facial Expressions

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- Identify Color, Hashtag and Captions
- Identify User General Content

4.3.1. Identify Facial Expressions

This chapter explains about the process and the methodology taken into consideration to design and develop the sentiment analysis in face book imagesfor depression detection system using facial expressions.

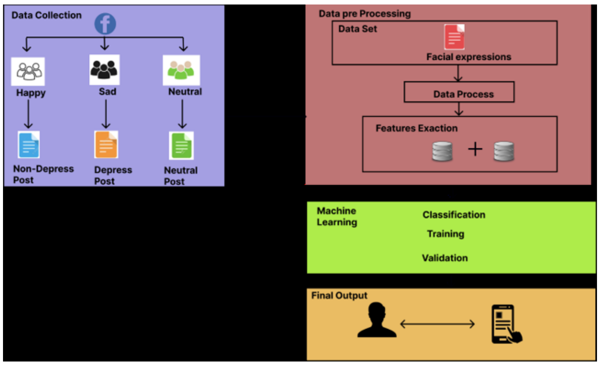

Figure 1: System overview of Identify Facial Expressions

In this data collection section, we consider users face book images, then collect these kinds of data. After that categorize in to three or four types according to facial expressions. Then do sentiment analysis, when a person uploads a picture with sad facial expressions or happy, we can categorize his emotional state at this time.

Next section is Data pre-processing part, before we collected some data set, it is including various kind of user's images. Then collected data set, we process the data. using machine learning algorithms such as CNN, OpenCV, Haar Cascades classifiers etc.

Then go to machine learning model and train it using these three methods. Using facial expression recognition and sentiment analysis, classification, training, and validation are crucial steps in creating a depression detection system. The technique of categorizing an input, in this example, facial expressions, is known as classification. Each facial expression must be categorized by the system as either depressive or not. Machine learning methods, like convolutional neural networks (CNNs) or support vector machines (SVMs), can be trained on a dataset of labeled facial expressions to identify the patterns and attributes connected to sadness to achieve reliable classification.

To train the system to recognize the patterns and features connected to depression, a labeled dataset of facial expressions is fed to the machine learning algorithms. To increase the algorithm's precision and lower error rates, iterative refinement is used. The more data the system is educated on, the more effectively it should perform.

Validation is the process of assessing how well a machine learning model that has been trained performs on a different dataset of labeled facial expressions that it has never seen before. Utilizing evaluation metrics like accuracy, precision, recall, and F1 score, the model's performance is evaluated. To make sure that the trained model can generalize to new data well and is not overfitting to the training dataset, the validation procedure is essential.

Using facial expression recognition and sentiment analysis, classification, training, and validation are crucial elements in creating an accurate and dependable depression. detection system. These procedures guarantee that the system can recognize facial expressions with accuracy, pick up on depression-related patterns, and generalize well to fresh data. In this final step, the system is identified as the possibility of having those who have depression symptoms using sentiment analysis based on facial expressions.

Generate depression rates according to sentiment analysis on the other hand provide consultant details to individuals identified as the possibility having those who are depression symptoms using sentiment analysis based on facial expressions and recommend some motivational videos for users.

4.3.2 Identify Color, Hashtag and Captions

This chapter explains the process and the methodology taken into consideration. to design and develop the sentiment analysis in face book images for depression detection system using color, hashtag, and captions.

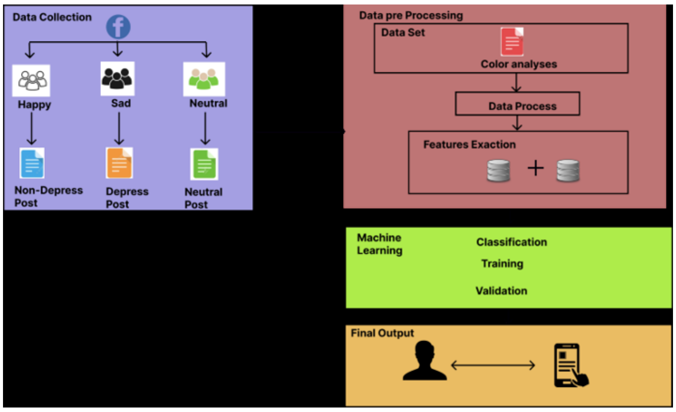

Figure 2: System overview of Identify Color, Hashtag and Captions

In this data collection section, we consider users captions color and hashtag face book images, then collect these kinds of data and the collected data comprises both textual and visual information. After that categorize into three or four types according to captions, hashtag, or color. Then do sentiment analysis, when person upload a picture with sad captions, hashtag or happy, we can categorize his emotional state at this time according to his captions, hashtags, and color of uploaded picture.

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Next section is Data pre-processing part, before we collected some data set, it is including various kind of user's text files and images. Then collected data set, we process the data. using machine learning algorithms such as NLP, TensorFlow and Python. For text classification using LSTM (Long ShortTerm Memory) neural networks. The goal of this code is to predict the emotions associated with a given caption or hashtag.

Then go to machine learning model, and train it using these three methods, such as classification, training, and validation. These are the crucial steps in creating a depression detection system. The technique of categorizing an input, in this example, texts are categorized into emotion states this is known as classification. Each text must be categorized by the system as either depressive or not. Sometimes we could not be able to directly identify the possibility of having a depression using color only. Therefore, in this research we are focused on combining color hashtag and caption-based identification.

Machine learning methods, like Natural Language Processing (NLP) or Long Shor Term Memory (LSTM) can be trained on a dataset of labeled facial expressions to identify the patterns and attributes connected to sadness to achieve reliable classification. To train the system to recognize the patterns and features connected to depression, a labeled dataset of captions, color and hashtags is fed to the machine learning algorithms.

Validation is the process of assessing how well a machine learning model that has been trained performs on a different dataset of labeled captions of face book images that it has never seen before. That the trained model can generalize new data well and is not overfitting to the training dataset, the validation procedure is essential. Using color, hashtags and captions recognition and sentiment analysis, classification, training, and validation are crucial elements in creating an accurate and dependable depression detection system.

In this final step, the system is identified as the possibility of having those who have depression symptoms using sentiment analysis based on combining color, hashtag, and captions. Generate depression rates according to sentiment analysis on the other hand provide consultant details to individuals identified as the possibility having those who are depression symptoms using sentiment analysis based on color and captions and recommend some motivational videos for users.

4.3.3 Identify User General Content

This chapter explains about the process and the methodology taken into consideration to design and develop the sentiment analysis in face book posts or images for depression detection system using comments, gif, stickers and emojis.

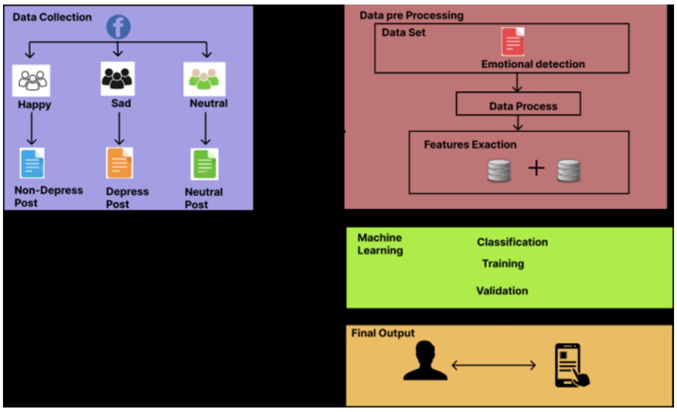

Figure 3: System overview of Identify Comments

According to this diagram, comments are analyzed on posts on social media networks such as Facebook. A doctor who uses the system adds his patient to Facebook private group created by doctor. After that, comment on the posts in the doctor group. Said in the patient's therapy. After the patient leaves a comment, MentiBot takes the input into the system. Hope to use image processing to input the comment.

The comment is received and then analyzed using an algorithm. Here the text, emojis, stickers, gifs in the comment are analyzed. Machine learning technique, NLP, classification methods are used for this. Text: Comments can be processed using standard natural language processing (NLP) techniques. You can tokenize the comments into individual words or phrases, remove stop words, and apply other preprocessing steps to prepare the text for sentiment analysis. Emojis: Emojis can be treated as separate tokens and processed in the same way as words.

You can use an emoji library to map each emoji to a specific code or token, and then tokenize the text accordingly. GIFs: GIFs can be treated as images and processed using object detection techniques. You can use a pre-trained object detection model to identify and extract the relevant GIFs from social media platforms, and then perform sentiment analysis on the extracted visual content.

After analyzing the comment, the sentiment in that comment is given. Here According to the comment made by the patient, the sentiment of the patient at that time is indicated. Accordingly, the sentiment is given as good, bad, and neural. After that, by examining the patient for a few days, it will be possible to show whether he/she has any symptoms of depression. Finally, if there is a state of depression at the end, the symptom is given through a GUI in the system.

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4.4 System Architecture

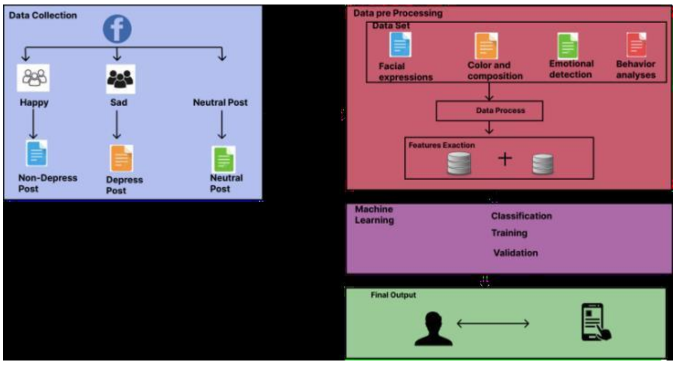

Figure 4: Overall System Diagram

According to this diagram explains the process and the methodology taken into consideration to design and develop the sentiment analysis in face book images for depression detection system. This discussion consists of the techniques, mechanism and requirement gathering. The main objective of this chapter is to provide methodology in brief regarding the research component, “Identifying facial expressions”.

In this concept, we expect to build an application that is suitable to use via smartphone and computer. Generate depression rates according to sentiment analysis on the other hand provide consultant details to individuals identified as the possibility having those who are depression symptoms using sentiment analysis based on these three components and recommend some motivational videos for users.

First and foremost, the system needs to guarantee that user data is kept private and secret. Only with the user's express agreement and in accordance with applicable data protection legislation can personal information about the user be disclosed. The system should also make sure that the consultant information is accurate, current, and credible.

Verifying the training, experience, and credentials of mental health practitioners is crucial, as is making sure they have the necessary licenses and certifications to offer mental health services. Thirdly, the system must provide simple and clear information regarding support groups and mental health services. It should be simple to comprehend and navigate and presented in an approachable way.

V. RESULTS AND DISCUSSIONS

In this research, the focus is on utilizing three components for sentiment analysis in the context of depression detection. The final output will be given as three outputs •Identified as the possibility of having those who are depression symptoms using sentiment analysis based on facial expressions •Provide Consultant Details •Recommend some motivational Video Series

5.1 Identifying Facial Expressions

Facial Expressions Sentiment analyzes in face book data for depression detection system using facial expressions. This MentiBot system will be directed into image processing. Using CNN (convolutional neural networks) algorithm, OpenCV, TensorFlow and Karas Libraries and ML techniques output will be directed to user friendly web application.

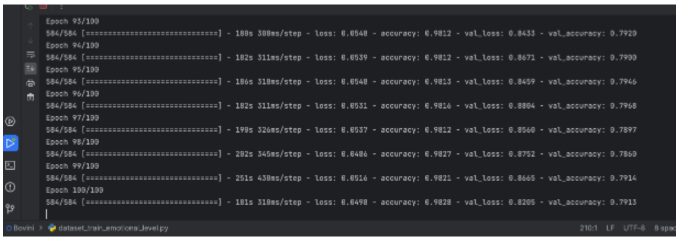

Figure 5: Training and Validation

In this part, there is a need of huge number of Facial expressions datasets to gain the best accuracy for the output. Therefore, we have referred to kaggle.com, and collected 46,000 images from this site. In this research, the model achieves a training accuracy of 65.28 percent and a validation accuracy of 34.72 percent, respectively. After each run, the model received training, and the accuracy of the outcome also increased with time. Following hundred runs, the training and validation accuracy increased to 0.20 percent and 98.28 percent, respectively. After training the model, prediction code will provide according to Identified facial expressions, when a person is hiding their face behind a mask or sunglasses.

5.2 Identifying Color, Hashtag and Captions

Sentiment analyzes in face book data for depression detection system using color, caption, and hashtag.

This MentiBot system will be directed into text recognition. Using NLP (Natural Language Processing) algorithm and for text classification using LSTM (Long Short-Term Memory) neural networks. Phyton is used for color analysis.

Figure 6: Training and Validation

In this part, there is a need for a huge number of Captions and hashtags datasets to gain the best accuracy for the output. Therefore, we have referred to kaggle.com, and collected 15,000 texts from this site. First, we type some captions and get

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an output and this result displayed as positive or negative or neutral according to train the model. After each run, the model received training, and the accuracy of the outcome also increased with time. Following a hundred runs, the training and validation accuracy increased to 0.60 percent and 94.28 percent, respectively. After training the model, the prediction code will provide according to identified combining color, hashtag and caption-based.

5.3 Identifying User General Content

Sentiment analyzes in face book data for depression detection system using comments, stickers and emojis. This MentiBot system will be directed into text recognition and visual elements recognition. Using NLP (Natural Language Processing) algorithm and for text classification using LSTM (Long Short-Term Memory) neural networks for text recognition and Using CNN (convolutional neural networks) algorithm for identifying emoji and stickers.

Figure 7: Identify Comments

In this part, there is a need for a huge number of Sinhala comments, emojis and stickers datasets to gain the best accuracy for the output. Therefore, we have referred to kaggle.com, collected 30,000 texts and visual elements from this site. First, we type some Sinhala comment with emoji or stickers and get an output and this result displayed as positive or negative or neutral according to train the model. After each run, the model received training, and the accuracy of the outcome also increased with time. Following hundred runs, the training and validation accuracy increased to 0.40 percent and 96.28 percent, respectively. After training the model, the prediction code will provide according to identified Sinhala comments, emojis and stickers.

V. CONCLUSION

This research paper discusses the use of social media sentiment analysis for depression detection systems. It offers benefits such as collecting large amounts of data, identifying potential depressive symptoms, and being non-intrusive. Sentiment analysis uses natural language processing to automate the process, allowing for faster and more effective study of social media data. Integrating sentiment analysis into depression detection systems could improve early detection and intervention, potentially reducing depressive episodes and improving outcomes.

However, limitations such as the complexityof human emotions and potential misinterpretations, false positives, and false negatives must be addressed to ensure the safety of personal information and ethical usage of social media data. Finally, all these system components will be controlled and monitored through the user-friendly application.

VI. FUTURE SCOPE

The future of sentiment analysis in the context of depression detection on social media platforms is poised for significant advancements and a broader scope. Multimodal analysis, encompassing not only text but also images and videos, will provide a more comprehensive understanding of users' emotional states. Contextual analysis will become more refined, enabling algorithms to better recognize sarcasm, irony, and nuanced expressions. The horizon of analysis will expand to include a wider range of languages, promoting inclusivity and cultural sensitivity.

Moreover, real-time monitoring capabilities will be a focus, offering immediate alerts and support to users displaying severe depressive symptoms, potentially preventing crises. Privacy preservation will remain at the forefront, ensuring that sentiment analysis respects user privacy and complies with stringent data protection regulations.

Longitudinal analysis will be a powerful tool, offering insights into the development and progression of depression. These insights will help track the effectiveness of interventions and treatments over time. The integration of sentiment analysis with mental health services will become even more seamless, facilitating referrals, immediate support, and connections to mental health professionals for those in need.

Furthermore, the field of sentiment analysis will extend its impact to address global mental health challenges. By identifying trends and hotspots related to mental health issues on a global scale, it can inform targeted interventions and awareness campaigns. Collaboration between data scientists, mental health professionals, and social media platforms will continue to refine the accuracy and ethical use of sentiment analysis for depression detection.

As we move forward, sentiment analysis systems will not only detect depression but also offer immediate AI-driven support, such as suggesting self-help resources, online therapy options, or crisis helplines. Education and awareness about mental health will also be a significant component, with tools that educate users about mental health and the importance of seeking help when needed. The future is bright for sentiment analysis in social media data, holding the potential to make a significant impact on mental health awareness and support.

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AUTHORS BIOGRAPHY

Mr. N.H.P. Ravi Supunya Swarnakantha,
Supervisor,
Faculty of Computing,
Sri Lanka Institute of Information and Technology,
Southern Province,
Sri Lanka

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Mrs. Bhagyanie Chathurika
Co-Supervisor,
Faculty of Computing,
Sri Lanka Institute of Information and Technology,
Southern Province,
Sri Lanka.

Subasinghe B.N.W
Undergraduate Student,
Faculty of Computing,
Sri Lanka Institute of Information and Technology,
Southern Province,
Sri Lanka.

Aththanayake K.A
Undergraduate Student,
Faculty of Computing,
Sri Lanka Institute of Information and Technology,
Western Province,
Sri Lanka.

Waidyarathne W.D.M.U.P
Undergraduate Student,
Faculty of Computing,
Sri Lanka Institute of Information and Technology,
North-Western Province,
Sri Lanka.

G.A Asahara
Undergraduate Student,
Faculty of Computing,
Sri Lanka Institute of Information and Technology,
Sabaragamuwa Province,
Sri Lanka.

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