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Predicting depression and suicidal tendencies by analyzing online activities using machine learning in android devices

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ABSTRACT

Artificial Intelligence (AI) has brought about a profound transformation in the realm of technology, with Machine Learning (ML) within AI playing a crucial role in today's healthcare systems. Advanced systems with intellectual abilities resembling those of humans are being created and utilized to carry out intricate tasks. Applications like Object recognition, classification, Optical Character Recognition (OCR), Natural Language processing (NLP), among others, have started producing magnificent results with algorithms trained on humongous data readily available these days. Keeping in view the socio-economic implications of the pandemic threat posed to the world by COVID-19, this research aims at improving the quality of life of people suffering from mild depression by timely diagnosing the symptoms using AI in android devices, especially phones. In cases of severe depression, which is highly likely to lead to suicide, valuable lives can also be saved if adequate help can be dispatched to such patients within time. This can be achieved using automatic analysis of users' data including text messages, emails, voice calls and internet search history, among other mobile phone activities, using Text mining/ text analytics which is the process of deriving meaningful information from natural language text. Machine Learning models analyse the users' behaviour continuously from text and voice communications and data, thereby identifying if there are any negative tendencies in the behaviour over a certain period of time, and by using this information make inferences about the mental health state of the patient and instantly request appropriate healthcare before it is too late. In this research, an android application capable of performing the aforementioned tasks in real-time has been developed and tested for various performance features with an average accuracy of 95%.

1. Introduction

Depression is a common and very serious, yet treatable, medical illness that affects patients' quality of life. It has a negative impact on what you think, feel or do, causing patients suffering from it to feel dismal or lose interest in everyday activities. Its causes are widespread, ranging from hereditary, along with relation to pessimistic personalities, to environmental factors, such as long-term exposure to violence, neglect, abuse or poverty. It can even affect people living in relatively ideal circumstances. In its severe state, it can even lead to suicide, which is one of the leading causes of death in the developed countries.

Identifying an individual's state of mind can greatly assist in improved quality of life and can serve as an important means of suicide prevention in extreme cases of depression. This study aims at achieving this cause with the help of an android application designed to analyze a person's behavior and mental condition using AI. An android phone user's text and voice communication, along with internet search history can be analyzed with the help of machine learning by training and deploying custom TensorFlow models in an android application. The timely predictions from such intelligent systems about a suspected volatile outburst from an individual can assist in launching adequate help in order to prevent suicides in extreme cases, or to improve quality of life in mild cases. System block schematic is given in Fig. 1. The data acquired from phones are processed locally to ensure users' privacy and reduce network usage thereby making the system cost efficient and secure.

In the proposed system a TensorFlow model is trained using NLP which is interfaced with the mobile application for the continuous monitoring of voice calls, text messages, emails, audio recordings and other search history for depression detection.

The organization of the paper is such that the work related to depression and technological developments for assisting such patients with the role of artificial intelligence is discussed in Section 2. Section 3 provides information of the equipment, algorithm, experimental setup and implementation methodology of Android application for depression detection. Section 4 evaluates the performance of the developed system and presents the results whereas the paper is concluded in Section 5.

2. Literature Review

For more than a decade, incredible research has been carried out in the field of human health monitoring systems, both physical and mental. Scientists and researchers have designed and developed systems for human sentiment analysis and mental health using a wide range of techniques including EEG, ECG, blood pressure, skin conductance, heart rate, facial expression detection and Natural Language Processing. This section skims through some of the existing technologies pertaining to identification and assistance of patients with Major Depressive Disorders.

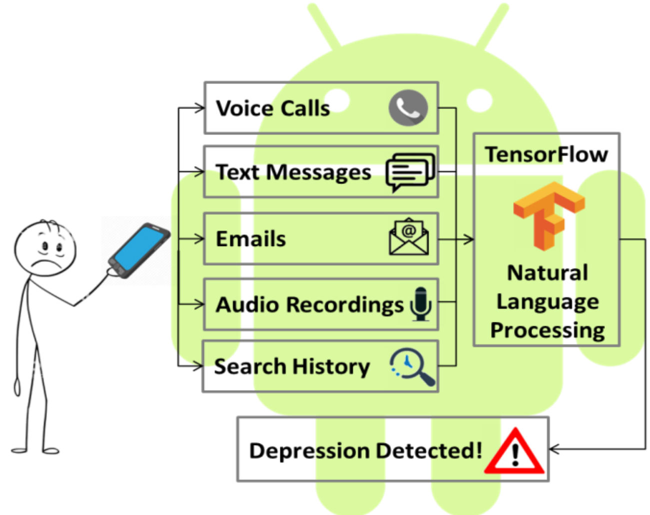


Fig. 1. Block schematic

The importance of social media as the premier source of information and communication of modern ages is presented in [1]. They have developed a system to predict depression from tweets using Bag of Words approach with a corpus of 2.5 M tweets. A similar study is seen in [2] where the researchers have developed a sentiment analysis system using Support Vector Machine and Naive-Bayes classifier to detect depression in tweets. [3] also proposed a similar model on Facebook where AI is used to detect suicidal tendencies in videos and posts. The limitation here is the use of only one social platform rather than a generic design that encompasses all user interactions for a comprehensive understanding of the users' state of mind. [4] and [5] studied the role of mobile phone technology in understanding and preventing suicidal behaviors. The authors proposed that data collection from mobile phones can prove to be fruitful in understanding transitions from suicidal thoughts to behaviors. The use of smart devices for psychological studies becomes the foundation of our research. The authors in [6] have developed Big Black Dog, a smartphone-based system to monitor sleep and social behaviors to infer the onset of depression. The developed app considers data from the smartphone sensors like Wi-Fi, accelerometer, call logs, luminous intensities, among others to evaluate behavioral patterns of the user. The Natural Language Processing aspect is completely missing in this research. Keeping Affective Computing in focus, [7] presented a survey of various emotional analysis models such as text, audio, video, social networks, facial expressions and physiological analysis, among others. [8] provided a comprehensive review of top-rated Android and iOS apps for depression available till spring 2019. The conclusion drawn from the survey indicates that 83% of such apps only offer interventions, suggesting that there is enough room for research and development of apps to continuously monitor user data to detect inclinations towards depression or suicidal tendencies. [9] proposed the study of suicidology and how smartphones and such digital technologies can help to gather data to assist in its prevention. [10] presented evaluation of an AI-enabled, empathetic, text-based conversational mobile mental well-being app, Wysa, on real-time data. Although this app works to monitor, evaluate and assist patients with depression using text conversations, it takes up extra time of the user to engage in questions and answers with the Artificially Intelligent chat-bot. A similar idea is also presented in [11] and [12]. In [13], a smart phone application based on Natural Language Processing (NLP) and Machine Learning (ML) model is used to identify suicide risk, but it's based on only voice and was tested in outpatient therapy sessions while in [14] authors used coarse-grained meta-data of Internet traffic on smartphones for depression screening in which they analyzed whether the user is depressed or not by using a dataset of 79 students of the University of Connecticut. Our research does not offer intervention sessions but monitors and evaluates users' mental health without dedicated question and answer sessions and just by analyzing day-to-day conversions with friends and family and other online activities continuously, in the background, making it very time efficient. The researchers in [15] have proposed fusion of audio, video and semantic features for detection of depression, but they have also used Question/Answer pairs and interviews for semantic content feature extraction. A similar endeavor is seen in [16] which works with self-assessment and sensor data. [17] have developed an Android app to detect Postpartum depression using different Machine Learning models, but the user has to interact with its GUI and answer questions in order for the app to make predictions, unlike our product, which keeps running in the background without interfering with the user. [18] reviewed a number of available mobile phone applications for suicide prevention but most of them just provide supporting and educational information to users, access to helplines, and offer counselling services via text messages or emails, whereas only a few offer risk analysis but based on pre-defined questionnaires [19]. [20] presented the use of mobile apps accompanied by an armband to monitor sleep, appetite and emotional state of the user. This is done by answers provided by the user to the questions put by the app along with monitoring of users' electromagnetic activity by wearable tracker band. The uneasiness of putting a device (electrodes) on the users' body along with investing time in answering periodic questions make this app tedious to use. [21] and [22] study mood disorders specially in bipolar disorder patients with the help of Android apps. [21] used PSYCHE Platform System. [23] which used features like, voice recorder, sensor activity, mood and sleep agenda, medication, etc. in a GUI to judge the patient's mental state, whereas [22] considered parameters like duration of phone calls and call logs to make such assessments. The surveys, interviews and study in [24] proposed that AI may be useful in suicide prediction. A similar review in [25] suggested that mobile technology and apps along with Machine Learning can play a vital role in this endeavor. [26] addressed early detection of depression using Convolutional Neural Networks and Natural Language Processing on text messages on a social platform. [27] proposed hunting for suicide notes in the web by using a dictionary of suicide related key-words. [28] studied search trends preceding increases in suicide with the help of monthly Google search volumes. The statistics provided in such studies encourage the integration of Internet search history for depression detection in our developed app. [29] introduced an AI chatbot employing a Hybrid Model that utilizes Natural Language Processing (NLP) to detect depression in the context of mental healthcare. Meanwhile, [30] put forward a method for detecting depression using two-lead ECG signals through a one-dimensional convolutional neural network. However, their system was found to be neither user-friendly nor cost-effective. Similarly, [31] proposed an approach for depression detection using EEG data. Additionally, [32] put forth a model based on NLP, which was trained using various textual sources such as social media posts, interviews, and clinical notes, to identify signs of depression. A convolutional neural network based approach is used to identify the wheat disease in [33]. By using the miniImageNet dataset and the omniglot dataset, a conv4 network is designed to extract the class features to make the predictions is proposed in [34]. [35] proposed gradient weighted class activation mapping and reinforcement learning based object detection techniques by following ResNet for remote sensing images which contains important information such as airports, ports and ships. [36] proposed a federated learning approach based on priori knowledge and a bilateral segmentation network for image edge extraction to improve the problem of data islanding.

The related work shows the different methodologies for the depression analysis because it's very important to avoid sudden suicides of the loved ones. As compared to the related work our proposed system is very simple because it does not ask any questions for the depression detection. It only processes the voice calls, text messages, emails, audio recordings and search history by using a TensorFlow model to analyze the depression.

3. Methodology

The major work in the materialization of this project has been carried out on Android studio using Infinix Hot 4 as the deployment hardware. An Android Virtual Device (AVD) Google Pixel has also been used during algorithm development and testing. The hardware and software used in the development of this project are given in section 3.1

3.1 Hardware and Software Specifications

The specifications of the workstation and phone used in the development process are given in Table 1. The algorithm was developed in Android Studio with support from TensorFlow, Google Firebase and Python. The major software and libraries used in this project are listed in Table 2.

Table 1

Hardware Specification

Hardware	
Workstation	
Model	Lenovo Legion Y545
CPU	Intel i7-9750H 2.6G (9th Generation)
GPU	Nvidia GeForce GTX 1660Ti 6 GB
RAM	16GB
Storage	1TB HHD + 512GB SSD
OS	Windows 10 Home
Smart Phone	
Model	Infinix HOT4 LTE
CPU	Quad-core 1.3 GHz Cortex-A7
GPU	Mali-400MP2
RAM	2GB
Storage	16GB
OS	Android 6.0 (Marshmallow)

Table 2

Software and Libraries

Software	Version
Android Studio	4.1.1
Python	3.7.6
PyCharm	2020.3.2
TensorFlow	1.14
TensorFlow-GPU	1.14
TensorBoard	1.14
Nvidia CUDA	10.0
CuDNN	7.4.1
NLTK	3.5
Bazel	0.24.1
Google Pixel (AVD)	OS Android 9.0

3.2 Project Modules

This project consists of the following major components which need to be designed and implemented separately, followed by the system integration.

3.2.1 Accessing test messages, emails, browser history, voice data from android phone

Android studio offers interaction with different applications and hardware sensors available on the phone, with your custom developed app, with the permission of the user. This feature will be used to access Internet browsing history, text messages, voice calls, along with other useful data for the development of this application. Analysis of the acquired data by the developed ML models will help in understanding the mental health of the user of the device. To keep the discussion succinct, the acquisition and analysis of only text (sent) messages is given here. The following java code snippet shows how this is achieved. Once the raw text data has been extracted, the pre-processing steps that follow are given in Fig. 2.

```
private String getSms() {
    String msgData = "";
    Cursor cursor =
getContentResolver().query(Uri.parse("content://sms/se
nt"),   null, null, null, "date DESC");

    if (cursor.moveToFirst()) {
      do {
        msgData += " "  + cursor.getString(13);
       } while (cursor.moveToNext());
    }
    return msgData;
```

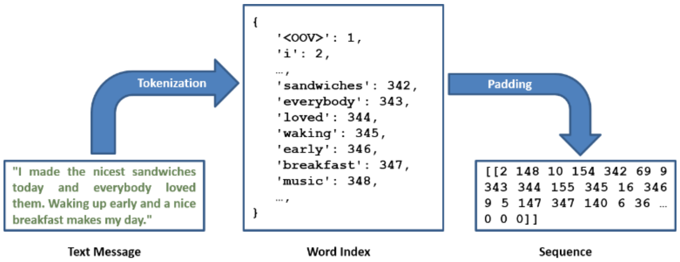


Fig. 2. Data Pre-Processing

3.2.2 *Machine Learning model for text analysis*

This section includes the study of the patterns in text communication data, internet search trends and other online communication, observed in patients suffering from depression. The trends in such data of patients before committing suicide are also studied and a database is constructed for the training of the Machine Learning model. The trained model is later extracted for use in the android application to make suitable inferences based on real-time data of the users.

3.2.2.1 *Text dataset*

The dataset used in this research is a collection of datasets including Reddit Self-reported Depression Diagnosis (RSSD) dataset received by Georgetown University, Washington DC, USA which contains Reddit user's posts and divided into 9,210 depressed users and 107,274 control users (Not depressed) [29]. The RSSD dataset is further divided into training, testing and validation as shown in Table 3. We have taken some portion of text from it which includes 2000 depressed and 2000 not depressed texts with an addition of our own custom depressed and happy texts of 2000 posts to cater for local word choice, sentence structures and preferences for the training of text classifier. This diverse dataset can enable us to make accurate inferences for users communicating in English across the globe with consideration to the region-specific slangs. The language pool can be enhanced in the future releases of the developed app. Fig. 3 shows the wordclouds for both depressed and happy categories using a subset of the dataset used in this prototype.

(a) Depressed (b) Happy

Fig. 3. Wordclouds

Table 3

RSSD Dataset

	Diagnosed Users (Depressed)	Control Users (Not Depressed)
Training	3070	35753
Validation	3070	35746
Testing	3070	35775
Total	9210	107274

3.2.2.2 *Text dataset for training*

The dataset assembled in the section 3.2.2.1 is then labelled into Depressed and Not Depressed classes and is further split into training, testing and validation sets. To keep the model fast and light, the input to the model is limited to 256 words only and the output has one class. If a text message has words less than 256 then zeros are padded to complete the word count. Also, in case the message's word count exceeds 256, then surplus words are discarded. Only text-based model was trained in this research and speech inputs were converted to text before processing using Google Speech to Text API, thereby increasing the efficiency and reducing the app size. Training has been carried out using Keras and Python.

The text messages are preprocessed initially, with the punctuations removed, conversion to lower case, tokenization, discarding the stop-words, stemming and lemmatization. This is followed by dictionary creation and word to index mapping to facilitate training. The vocabulary size (dictionary) has been limited to 88000 words. After completion of the preliminary preprocessing steps, the Keras model is developed with an input layer of shape 256, an Embedding layer, a GlobalMaxPooling1D layer, a Dense layer with a Rectified Linear Unit (relu) as an activation function and an output layer for classification/ predictions with a sigmoid activation function. The model is then complied using binary-crossentropy and an adam optimizer. The summary of the trained model is given in Fig. 4. The epochs, batch size and validation data are setup, and the model is evaluated on the test dataset to provide accuracies stated in Table 4.

At the end of the training and validation process, the "h5" file hoding the Keras model parameters is created which is later converted to "tflite" for mobile deployment.

```
Model: "sequential"
_________________________________________________________________
Layer (type)                Output Shape              Param #
=================================================================
embedding (Embedding)       (None, 256, 16)           1408000

flatten (Flatten)           (None, 4096)              0

dense (Dense)               (None, 6)                 24582

dense_1 (Dense)             (None, 1)                 7

=================================================================
Total params: 1,432,589
Trainable params: 1,432,589
Non-trainable params: 0
_________________________________________________________________
```

Fig. 4. Model Summary

Table 4

RSSD Dataset

S. No.	Dataset	Accuracy	Loss
1	Training	90%	0.0691
2	Validation	95.4%	0.092
3	Testing	92.9%	0.105

3.2.3 Custom TensorFlow lite model of android

TensorFlow Lite is an open-source deep learning framework for on-device inference. It is used to deploy machine learning models on mobile and IoT devices. The custom TensorFlow models trained in sections 3.2.2 is then converted to TF-lite and packaged into an android app using google Firebase ML-kit for real-time on device fast and accurate results. The internal mechanics of the tflite model is shown in Fig. 5. The tflite conversion process in python is shown in the flowing code snippet:

```
converter =
tf.lite.TFLiteConverter.from_keras_model_file('depress
ion_model.h5',input_shapes={'embedding_input': [1,
256]})
depression_tflite_model = converter.convert()
# Save the model.
with open('depression.tflite', 'wb') as f:
  f.write(depresseion_tflite_model)
```

Firebase is a platform developed by Google for creating mobile and web applications. Hosting the tflite model on Firebase proves to be an efficient way to update and modify your tflite models which are automatically downloaded by the users at run-time without having to modify the app itself. In addition to the tflite model, a JavaScript Object Notation (JSON) file containing word-index dictionary is also created to be incorporated in the assets of the Android app for adequate text pre-processing in Java. The following code snippet shows how this is done.

```
with open( 'word_dict.json' , 'w' ) as file:
  json.dump( word_index , file )
```

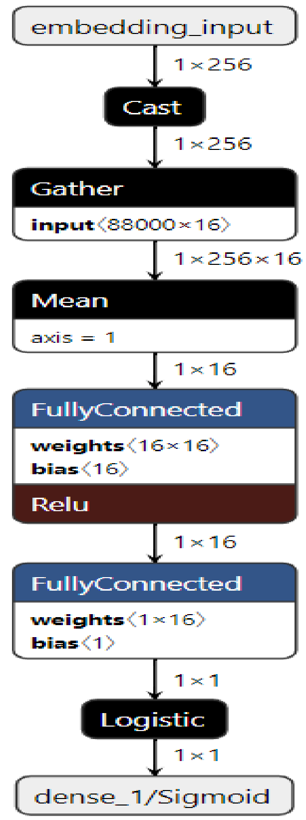


Fig. 5. Tflite model

3.2.4 Android App Development

Android studio is the official integrated development environment for app development for Android operating system. Its GUI development, along with other features have been used with Java as the principal language for coding, in addition to the features offered by Google Firebase. The final product of this research is a fully functional Android application which can be made available on Android play-store for public use. Fig. 6 depicts the development stages of this application, whereas the operational flow of the app is given in Fig. 7.

3.2.5 Real-time testing of developed app on actual phone data

In the final phase of this project, the developed application has been tested on 20 subjects over a period of time to observe the accuracy of the deployed ML model. A subset of the results is provided in table 5. Consultation with a physician/ psychologist and test on actual depression patients to validate the model and the developed app is yet to be done.

Table 5

Testing Results

S. No.	Test Subject	Gender	Age	Duration of use	App Inference	Mental/ Physical state of test subject revealed during interview
1	Student	Male	23	1 Day	Not Depressed	Happy, Healthy
2	Student	Female	24	1 Day	Not Depressed	Happy, Healthy
3	Student	Male	24	1 Day	Depressed	Happy, Healthy
4	Student	Male	25	1 Day	Depressed	Stressed due to positive Covid-19
5	Student	Female	23	1 Day	Depressed	Stressed due to exams
6	Student	Female	26	1 Day	Not Depressed	Happy, Healthy
7	Student	Female	26	1 Day	Depressed	Stressed due to family issues
8	Faculty	Male	35	7 Days	Depressed	Stressed due to family issues
9	Faculty	Female	30	3 Days	Not Depressed	Stressed due to family issues
10	Faculty	Male	30	1 Day	Not Depressed	Happy, Healthy

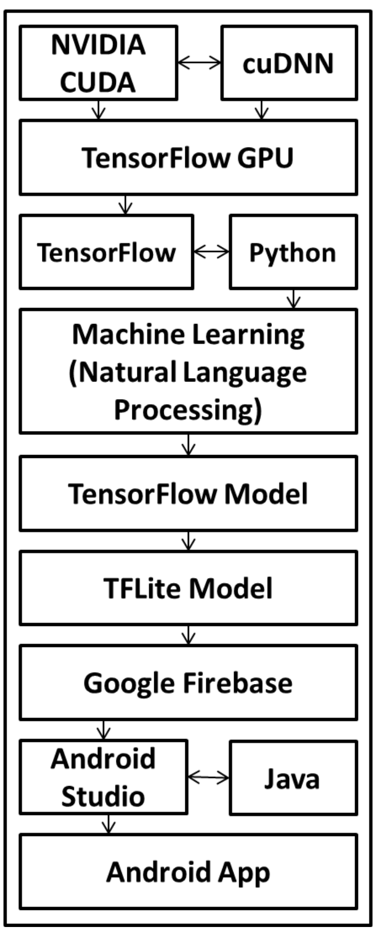


Fig. 6. Development flow

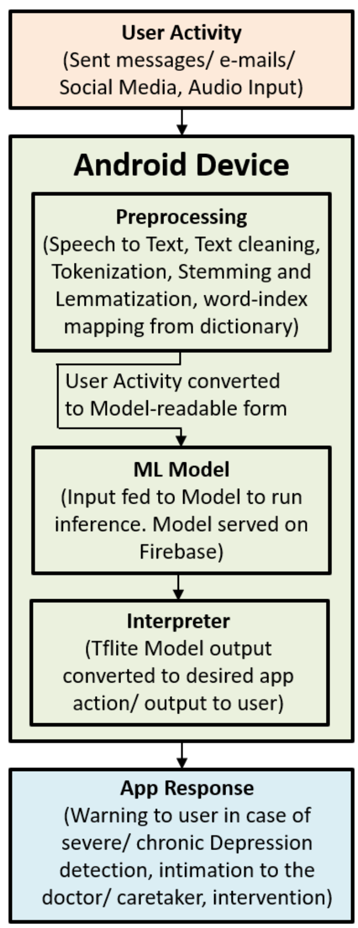


Fig. 7. Operational Flow

4. Results and Discussion

The performance evaluation of the developed system with respect to speed and accuracy is discussed in this section.

4.1 Confusion Matrix

The confusion matrix given in Fig. 8 is the output of testing the trained model on the test dataset which contains 600 posts, spilt equally into Depressed and Not Depressed. It can be observed from the confusion matrix that from 300 posts of Depressed only 17 False Negative (FN) outcomes were found and from 300 posts of Not Depressed only 12 False Positive (FP) outcomes were found which represents that the average accuracy of the trained model is 95%.

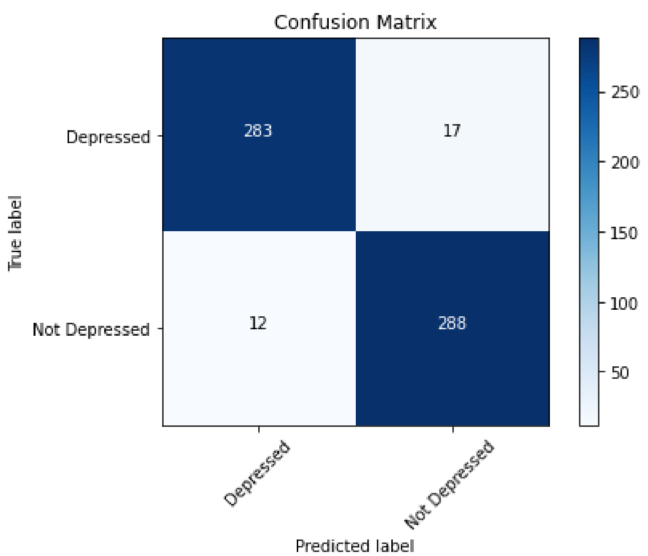
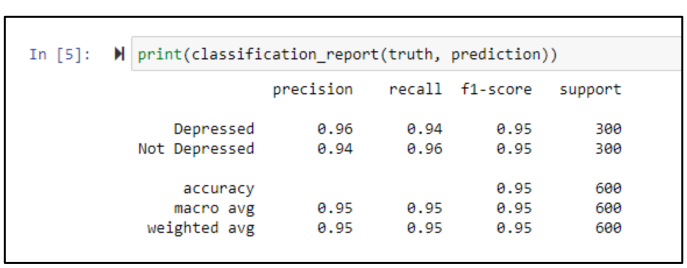


Fig. 8 Confusion Matrix

4.2 Classification Report

The overall performance parameters such as precision, recall, f1-score and the accuracy of the trained model on the test dataset is given in the classification report as shown in Fig. 9.



```
In [5]:  print(classification_report(truth, prediction))

               precision    recall  f1-score   support

    Depressed       0.96      0.94      0.95       300
Not Depressed       0.94      0.96      0.95       300

     accuracy                           0.95       600
    macro avg       0.95      0.95      0.95       600
 weighted avg       0.95      0.95      0.95       600
```

Fig. 9. Classification Report

4.3 User Interface (UI)

The UI of the developed app with two instances of text classification is given in Fig. 10. The output of the developed Android Application on various samples of Text data is depicted in Table 6.

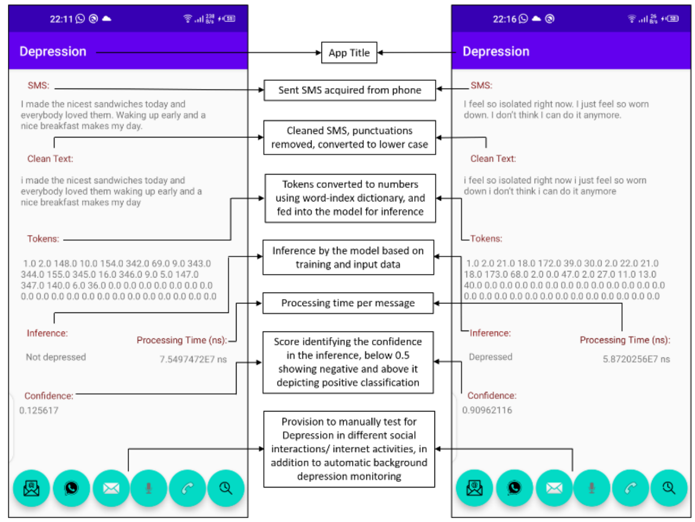


Fig. 10. Depression App User Interface

Table 6

Output of the Developed Android Application

Input Data	Sequence	Inference	Result
"I made the nicest sandwiches today and everybody loved them. Waking up early and a nice breakfast makes my day."	[[2 148 10 154 342 69 9 343 344 155 345 16 346 9 5 147 347 140 6 36 … 0 0 0 0]]	0.125617	Not Depressed
"life is simply awesome every day amazing"	[[15 4 1 142 74 36 62 … 0 0 0 0]]	0.08727707	Not Depressed
"i am very sad all the time and i want to kill myself"	[[2 12 288 66 56 10 78 9 2 26 3 64 119 … 0 0 0 0]]	0.94697	Depressed
"I feel so isolated right now. I just feel so worn down. I don't think I can do it anymore."	[[2 21 18 172 39 30 2 22 21 18 173 68 2 1 47 2 27 11 13 40 … 0 0 0 0]]	0.90962116	Depressed

4.4 Speed

The time taken to process an individual text message on different android devices along with the AVD is shown in Fig. 11. It can be observed that the processing and inference acquisition time depends on the processing capabilities of the devices running the app and is extremely fast which makes the developed application deployable in real-time.

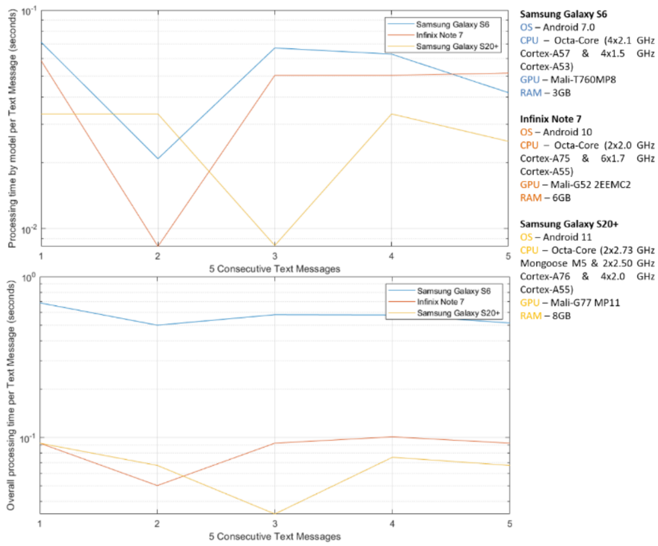


Fig. 11. Processing Time

4.5 Comparative Analysis

The comparative analysis of the proposed system is mentioned in Table 7. It has been found that the proposed system is based on the role of mobile phone technology in understanding and preventing suicidal behaviors because now a days smartphone is the only gadget which is 24/7 available to everybody.

The proposed system is when compared to existing systems that utilize EEG, ECG, blood pressure, skin conductance, heart rate, facial expression recognition, and Natural Language Processing, it was determined that the proposed system offers superior accuracy while maintaining affordability and a user-friendly interface for detecting depression levels. It is also found more robust with multiple features because it monitors voice calls, text messages, emails, audio recordings and other search history but the discussed techniques only monitor single feature as given in table 7. The proposed system is automatic, robust and user friendly because it does not have any question answer session of the prediction of depression.

Table 7

Comparative analysis of the proposed system with the existing systems

Reference	Features	Cost	Accuracy	Usability
[1]	Tweeter tweets	Low	High	Good
[3]	Facebook posts	Low	High	Better
[10]	Questions/Answers	Low	Low	Better
[13]	Voice	Low	High	Best
[22]	Phone calls	Low	High	Better
[28]	Google search volumes	Low	Low	Good
[29]	Natural language processing	Low	High	Good
[30]	ECG	High	High	Best
[31]	EEG	High	High	Best
[37]	Heart Rate	High	High	Better
[38]	Facial Expression	High	Low	Good
[39]	Heart Rate, Skin Conductance	High	High	Good
Proposed	voice calls, text messages, emails, audio recordings and other search history	Low	High	Best

5. Conclusion

The developed app produced satisfactory results on input testing data, with reasonable processing speed and accuracy. The on-device deployment and processing of Text Classification Model results in low-cost and high-privacy design since there is no need of internet after one-time downloading of the model on device which makes the network requirement of our developed app literally zero. The text classification models are relatively smaller in terms of disk-space requirements as compared to image classification and other models, resulting in low-disk space usage by our application. Users' consents to access text messages and other data, are also requested at the time of installation of the app. The users' privacy is of foremost importance and is upheld by all the processing occurring on-device and no information leaving the users' device at all. The depression detection model was trained on the subset of datasets given in section 3.2.2.1 and the performance of the developed model has vast room for improvement by adding more data during the training phase. In addition, the use of Long Short-Term Memory recurrent neural networks, among others, can significantly improve the model's performance.

The degree of depression that a user is detected can be used to alert the user to seek professional help if found to be above alarming thresholds. In addition, an optional feature of adding the contact information of a loved one or a health professional is available, to whom an SMS or email is sent in case of extreme instability detection in a user. All the processing of users' information takes place in the background without hindering the daily normal activities of the user of the phone, thereby making this app extremely docile. As an extension to using NLP for analysis of a user's mental state, features like user's motion/ physical activities can also be monitored from phones sensors like accelerometer to get a bigger picture about the user's mental health paired with the information of physical activities. This application works on the sent messages and emails of the user, but as a future extension, it can also be programmed to analyze the incoming messages thereby identifying if any of your friends or family is suffering from depression or is vulnerable to extreme measures like committing suicide.

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