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Suicidal Tendency Detection Using Deep Learning Techniques

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ABSTRACT

Suicide is a major problem in todays society. Suicidal tendencies, or the intention to commit suicide or terminate ones life, are tragic circumstances that are typically unknown to anyone in the victim's life. Despite improvements in the detection and treatment of serious mental diseases, suicide has remained an unsolvable public health issue. Several studies have shown unequivocally that victims frequently commit suicide either to end their suffering or distress or to feel relieved that they would no longer have to live in this world. To save peoples lives, early detection, as well as prevention of suicide attempts, must be addressed. Clinical methods based on interactions between social workers or other experts and the individuals under observation are currently used to detect suicidal tendencies, as are machine learning techniques with feature engineering or deep learning for automatic detection based on the previously mentioned perspectives. The goal of this study is to suggest a technique that enables the victim's family, friends, or other close relatives to recognize early signs of depression. The primary objective is to establish a strong correlation between subsystem components as well as compare their accuracies in order to build an alarming system. "Better late than never," the suggested technique may rescue the victim and initiate immediate treatment. Unlike existing systems, this project is aimed at identifying suicidal tendencies from multiple perspectives rather than concentrating on only one. To facilitate future research, several specific tasks and datasets are introduced and summarised.

Keywords: - Convolutional Neural Networks, Random Forest, Human-Computer Interaction, Natural Language Processing, Text Tokenization through NL

I. INTRODUCTION

For a very long time, depression has been seen as a single illness with a set of diagnostic requirements. It frequently co-occurs with anxiety or other psychological and physical illnesses and affects how those afflicted feel and behave [1]. According to the WHO study, there are 322 million people estimated to suffer from depression, equivalent to 4.4% of the global population. Nearly half of the in-risk individuals live in South-East Asia (27%) and Western Pacific region (27%) including China and India [41]. In many nations depression is still under-diagnosed and left without any effective therapy that can result into an extreme self that can ultimately lead to suicide [2]. Suicide represents an important social issue. In accordance with the World Health Organization (WHO), nearly 700,000 million individuals worldwide commit suicide each year, and many more, particularly those in their twenties and thirties, attempt suicide [3]. Suicide is the second most common cause of death in people aged 10 to 34 [4]. Suicidal tendency, as well referred as suicidal ideation, refers to when a person thinks about self-harm. Suicidal ideation can impact individuals of every age for a wide range of reasons along with shock, anxiety, guilt, stress[32], and depression [31,34]. Long-term depression can result in suicide if sufficient treatment is not sought, despite the reality that a large percentage of people who have suicidal thoughts do not attempt suicide [5]. Medical professionals and pharmaceuticals can be used to reduce a person's predisposition towards suicide. However, because of the negative stigma connected with medical treatments, most people who have suicidal thoughts avoid them. This project intends to focus on people who intend to commit suicide. As a result, a multifaceted technique which can detect this tendency and notify family, friends, or close ones ahead of time can be a boon to the invention. The key element in this project is an electronic device, specifically a mobile phone (as used by the majority of them). This device is used to capture various elements such as facial gestures, speech recognition, and many others. A simple concept of incorporating various aspects such as Facial Gestures, Voice Recognition, and Messaging Patterns joins the bandwagon alongside the project's technical by-products. Unhappy facial expressions such as sad, dull, and tired are easy to recognise; voice patterns such as low voices that sound dull are easy to identify that someone is unhappy; Text messaging patterns that are unusual indicate a lack of interest in doing activities. According to one study, 78% of hospital inpatients who committed suicide denied having suicidal thoughts during their last verbal communication [9]. Thus, A novel, data-driven tool for analysing acute suicide risk is urgently needed. People have to anticipate not only who is at a greater chance of committing suicide in general, but also the time that person is at a higher risk [35]. The increased use of smartphones and information services such as email, blogs, crowd-sourcing sites, and social media has resulted in an increase in the volume of unstructured text data. Text mining techniques applied to person-generated data, such as text messages (i.e., short message service [SMS]), may reveal how communication patterns and media use change as an individual's risk state rises. (For example, [11] from depression to suicidal tendency to suicide attempt). As per Pew Research Centre, in the United States, 99% of Millennials are using the online services and 92% already have a smartphone[17]. Millennials, the first generation to be engrossed in the world of social media and technology [21], are indeed an extremely vulnerable population, as self-harm is the leading mortality rate for individuals aged 15 to 34 [6], [10].

II. RELATED WORKS

The check by the authors in their publication[29] is the first to completely describe and introduce the approaches from these areas. self-murder notes, electronic health records, questionnaires, and online stoner content are among the data sources used to estimate sphere-specific operations of suicidal creativity discovery. Clinical styles grounded on relations between social workers or other specialists and the individualities being covered are presently used to descry suicidal creativity, as are machine literacy ways with point engineering or deep literacy for automatic identification grounded on online social media. To prop unborn study, a number of particular tasks and datasets are introduced and summarised. They conclude by listing the limitations of the current study and outlining implicit unborn exploration options. Four areas make up the maturity of operations for detecting suicidal creativity questionnaires, electronic health records, self-murder notes, and online stoner material. Among these four crucial areas, questionnaires and electronic health records(EHRs) calculate heavily on social workers or other internal health professionals and demand tone- report dimension or case- clinician connections. self-murder notes have a limit on immediate forestalment since numerous people who essay self-murder do so shortly after writing a self-murder note. They do, still, offer a useful resource for content analysis and the disquisition of self-murder- related issues [39]. When combined with machine literacy approaches, the final online stoner content sphere offers a largely promising means of early discovery and self-murder forestalment. stoner- generated content will come more pivotal in the identification of suicidal creativity as a result of the rapid-fire advancement of digital technologies. In the future, it's extremely probable that other types of data, similar health data from wearables, will prop in the monitoring of self-murder threat. The limitations of this paper are the lack of data is the most important problem facing current exploration [42]. The maturity of current approaches uses supervised literacy strategies, which bear homemade reflection. To grease fresh exploration, there are not enough labelled data, however. To get the verity, there is not important substantiation to back up the self-murder move. Hence, using certain predefined reflection criteria and hand labelling, data are collected [44]. Reflections grounded on crowdsourcing may affect in prejudiced labelling. Shing et al [30]'s request for expert labelling redounded in a small number of labelled circumstances. For case, Nobles etal. [7] fitted word circumstance and psycholinguistic features into the multilayer perceptron(MLP). Convolutional neural networks (CNNs) and intermittent neural networks(RNNs) are two common types of deep neural networks(DNNs). With well- known word embedding styles like word2vec (8) and GloVe [12], natural language textbook is generally bedded into distributed vector space. Text dispatches were decoded using stoner-position CNN with sludge sizes of 3, 4, and 5 by Shing etal [13]. Textual sequences are decoded using a long short- term memory(LSTM) network, a well- liked RNN interpretation, and also reused for bracket using completely connected layers(14). New ways for detecting suicidal studies integrate DNNs with other slice- edge literacy paradigms. Ji et al [15]'s model aggregation approaches for CNNs and LSTMs, two types of neural networks, were suggested with the thing of relating suicidal intent in private converse apartments. Decentralized training, on the other hand, relies on fellow in converse apartments to label stoner posts for supervised training, which can only be used in the most introductory cases. Using unsupervised orsemi-supervised literacy ways could be a preferable option. By prognosticating the gender of druggies as a supplementary task, Benton etal [16] prognosticated self-murder attempt and internal health using neural models within the environment ofmulti-task literacy. In order to increase performance with a CNN model, Gaur etal [18] included external knowledge bases and a self-murder-related ontology into a textbook representation. A deep literacy model incorporating GloVe for word embedding, bidirectional LSTM for sequence encoding, and a tone-attention medium for relating the most instructional subsequence was created by Coppersmith etal [19]. LSTM, CNN, and RNN were employed by Sawhney etal [20] to descry suicidal creativity. Tadesse etal [28] also used the LSTM- CNN model. For garbling textbook and threat pointers, Ji etal [21] developed an attentive relation network with LSTM and content modelling. Some well- known DNN infrastructures were used in the 2019 CLPsych Shared Task [22]. Pretraining was examined by Hevia etal [23] employing a variety of models, including GRU- grounded RNN. Popular deep learning models like CNN, LSTM, and Neural Network conflation were examined by Morales etal [24](NeuNetS). Binary- environment modelling utilising crescively attentive RNN and BERT was proposed by Matero etal [25]. The so-called mongrel system, which combines representation literacy with minor point engineering, is another sub-direction. A mongrel categorization model of the behavioural model and the self-murder language model was put forth by Chen etal [26]. For categorising individualities who essay self-murder and have depression, Zhao etal [27] suggested the D- CNN model using word embedding and external irregular characteristics as inputs. When it comes to demographic information, the quality of the data on self-murder is worrisome, because the mortality estimate includes general mortality but not self-murder. Some incidents are inaptly labelled as accidents or deaths with unclear motives. Only a small portion of popular social media posts have self-murder intentions. still, rather than considering it as an unevenly distributed set of data, the maturity of exploration constructed datasets in an indeed fashion to gather roughly balanced positive and negative samples. Suicidal intent wasn't well understood by the being statistical literacy system. numerous cerebral factors have a part in tried self-murder [36]. Mainstream approaches, still, concentrate on choosing characteristics or employing sophisticated neural infrastructures to ameliorate the performance of vaticination. Machine literacy methodologies discovered statistical hints from the phenomenology of suicidal posts in social material. Unfortunately, despite including the psychology of self-murder, they were unfit to rationalise the threat factors.

III. METHODOLOGY

A. PROPOSED SCHEME

The goal of this study is to suggest a system that can identify suicidal tendencies using a variety of methods. To carry out a thorough execution, three technologies—Human Computer Interaction, Natural Language Processing, and voice pattern analysis—are taken into account. The implementation of a correlation matrix that can identify strong or weak correlations between the aforementioned three components is later suggested.It has the advantages of predicting outcomes from a variety of perspectives and providing accurate results thanks to a correlation matrix.The goal of this study is to show a fully functional device that can identify a suicide intention. The spectrum of intended outputs includes recording facial expressions and identifying the victim's utterances.We use Human Computer Interactions for Facial Gesture Detection, Natural Language Processing for Speech Recognition, and Text Tokenization via NL for Messaging Patterns. Text Pattern Recognition - TWINT is used to prepare the dataset before analysing non depressive data. These two sets of data are combined. TorchText is used for tokenization. Speech Pattern Recognition - Use the DAIC-WOZ dataset to separate audio signals into spectrograms. Create a CNN architecture and recognize lower frequencies patterns with CNN and SVM. Facial Gesture Recognition - Use the FER-2013 dataset to classify emotions using CNN architecture. Separate positive as well as negative emotions now. Use CNN on negative emotions to detect suicidal intent.

Text analysis (TA), a machine learning technique, is used to automatically extract helpful information from unstructured text input. Businesses utilize text analysis technologies to quickly absorb papers and web data and turn them into insightful information. Text analysis allows you to extract precise information from tens of thousands of emails, like names, company names, or keywords, and arrange survey responses by attitude and topic. Using specifically created algorithms, sound recognition (and voice recognition) recognizes patterns in audio signals. The algorithm then selects and groups data based on predetermined criteria or by using common parts and components. The algorithm also provides the opportunity for learning and improvement, which is essential for machine learning technology to produce results that are ever more accurate. The name itself provides the simplest explanation: it is used to identify sound patterns in collections of audio data. patterns that use a series of flat lines and spikes to convey stories about the data.As a computer-based technology, the facial expression recognition system uses algorithms to instantly detect faces, decode facial expressions, and identify emotional states. It accomplishes this by using computer-powered cameras mounted on computer screens, incorporated in laptops, smartphones, and digital signage systems, or cameras that are powered by batteries. Face detection, facial landmark detection, and facial expression and emotion classification are the general steps in facial analysis using computer-powered cameras.

B. ARCHITECTURE

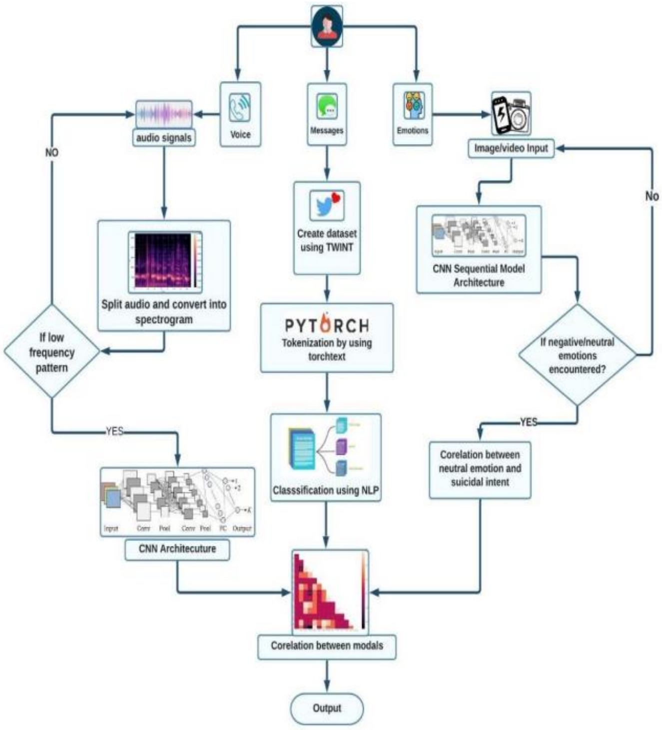

Fig.1 System Architecture

The system architecture, which consists of a few modules, some external hardware, and a database, is explained by the diagram above. The user enters the system and provides speech-based input. Messages are collected into a dataset using TWINT, tokenized using PyTorch, and then categorised using NLP. It is made up of divided audio signals that have been turned into spectrograms. Moreover, there is an image/video input. Finally, we discover a correlation between these elements.

C. DATA PRE-PROCESSING

We employ natural language processing to collect datasets for text message tokenization and speech recognition. The objective of natural language processing is to create machines that understand and respond to text or voice data by responding with spoken or written language of their own, much like humans do. The discipline of "artificial intelligence" (AI) called as "natural language processing" (NLP) in computer science is more specifically focused with giving computers the ability to perceive spoken and written words similarly to how humans do. Computational linguistics, which models human language using rules, is combined with statistical, machine learning, and deep learning models in NLP [37]. By making use of modern methods, computers can now fully know what's being said or written, along with the speaker's or writer's intents and sentiments, and interpret human language as a type of text or audio file. NLP is the driving force behind computer programs that can translate text between languages, respond to spoken requests, and summarise massive volumes of information quickly—even in real time. In the form of voice-activated Navigation systems, digital assistants, speech-to-text transcription programs client service chatbots, as well as other user conveniences, NLP [38] has likely been utilized us. The use of NLP in corporate solutions, however, is expanding as a means of enhancing worker productivity, streamlining vital business procedures, and streamlining daily operations. As human language is replete with ambiguity, it is incredibly difficult to develop software that accurately determines the actual message behind written or audio. A few examples of abnormalities in human language are plurals, sarcasm, riddles, illusions, deviations to use and grammar norms, and alterations in sentence structure. That takes a years to learn but that programmers must teach natural language-driven applications to recognize and understand accurately from the beginning if those applications are to be useful. Many NLP operations analyse human text and speech data in order to aid the computer in understanding the text and speech data it is ingesting. These are only a few of these jobs: The process of accurately translating voice data into text is known as speech recognition, commonly referred to as speech-to-text. Speech recognition must be used by any application that responds to questions or orders spoken aloud. Speech recognition is particularly challenging due to how quickly people speak, how they slur words together, how they emphasise and intonate their words differently, how they speak in different dialects, and how frequently they use poor grammar. For tackling particular NLP tasks, a variety of tools and libraries are available in the Python programming language. The Natural Language Toolkit(NLTK), an open-source collection of libraries, tools, and educational coffers for developing NLP programmes, contains several of them. The NLTK offers libraries for numerous of the below- mentioned NLP tasks as well as libraries for subtasks including judgment parsing, word segmentation, stemming and lemmatization (ways for removing all but the most essential letters from words), and tokenization(for breaking expressions, rulings, paragraphs and passages into commemoratives that help the computer more understand the textbook). also, it has libraries for enforcing functions like semantic logic, which allows druggies to draw logical consequences from textbook-grounded substantiation. The original NLP operations were hand- enciphered, rules- grounded systems that were able of carrying out certain NLP tasks, but they were unfit to fluently gauge to handle an supposedly noway - ending sluice of exceptions or the growing quantities of textbook and speech data. Enter statistical natural language processing (NLP), [33] which combines computer algorithms with deep literacy and machine literacy models to automatically prize, classify, and marker corridor of textbook and speech input previous to calculating the statistical probability of each conceivable interpretation. currently, deep literacy models and literacy styles grounded on convolutional neural networks(CNNs) and intermittent neural networks(RNNs) allow NLP systems to" learn" as they go on and prize ever- more-accurate meaning from massive quantities of unlabelled, unshaped textbook and voice data sets[40].

D. ALGORITHMS

In our model, we used different types of Machine Learning's Algorithms as well as Deep Learning Approaches. Machine literacy's general ideal is to comprehend data structure and incorporate data into models that people can comprehend and use. Machine literacy is a subfield of computer wisdom, but it differs from traditional computational ways. Algorithms are sets of purposefully drafted instructions that computers use to do computations or address issues in traditional computing. rather, machine literacy ways enable computers to train on data inputs and employ statistical analysis to produce values that fall inside a given range. Machine literacy makes it possible for computers to produce models from sample data in order to automate decision- making grounded on data inputs. Programs that use machine literacy can do tasks without having them explicitly enciphered. In order for computers to do specific jobs, they must learn from the data handed. For straightforward jobs given to computers, it's possible to produce algorithms that instruct the machine how to carry out all the way necessary to address the issue at hand without the need for the computer to learn. moment, machine literacy benefits every stoner of technology. Social networking platforms can help druggies in trailing and sharing images of musketeers thanks to facial recognition technologies. portable type is created using optic character recognition(OCR) technology from prints of textbooks and facial expressions. Machine literacy- grounded recommendation machines make recommendations for what

Human Computer Interaction(HCI) has helped to the design and development of several effective, user-friendly, cost-effective, and adaptive digital internal health results. Yet, HCI has not been well incorporated into technology advancements, raising issues with quality and safety(43). The vaticination, identification, collaboration, and treatment handed by internal health care and self-murder forestalment services could be bettered with the help of digital platforms and artificial intelligence(AI). Web- grounded and mobile apps are powered by AI, which is substantially utilised for tone- help and supervised Cognitive Behavioural remedy(CBT) for anxiety and depression. Real- time webbing and treatment in outmoded, overburdened, or underdeveloped internal healthcare systems may profit from interactive AI. Availability, efficacity, trust ability, utility, safety, security, ethics, applicable education and training, and sociocultural rigidity are some of the obstacles to the use of AI in internal healthcare.

pictures or television series to watch next grounded on stoner preferences. Soon, people might be suitable to buy tone-driving buses that use machine literacy to navigate. In this tutorial, we'll examine both supervised and unsupervised machine literacy ways as well as popular algorithmic approaches, similar to the k- nearest neighbour algorithm, decision tree literacy, and deep literacy. We will examine the most popular programming languages for machine literacy and bandy some of its advantages and disadvantages. We will also talk about impulses that are corroborated by machine literacy algorithms and suppose about how to avoid them when developing algorithms. Deep literacy has had tremendous success in a variety of fields, including computer vision, natural language processing, and medical opinion. It's a pivotal fashion for automatic suicidal creativity identification and self-murder forestalment in the field of self-murder exploration. It doesn't bear complex point engineering approaches to successfully learn textbook characteristics automatically as well as speech recognition can be done and it's decrypted in textbook format. also, some people feed uprooted data into deep neural networks.

1) Support Vector Machine:

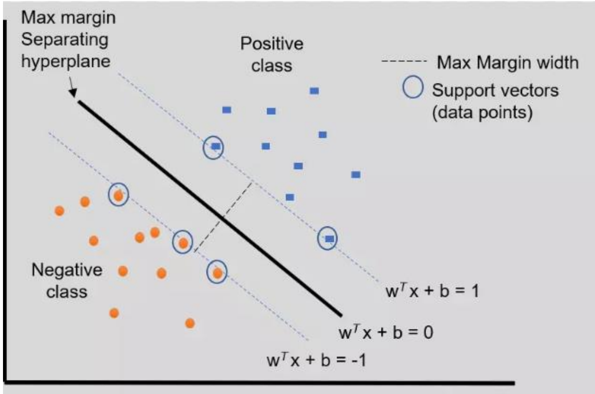

Fig.2 Support Vector Machine

Support vector machines are supervised literacy ways used for outlier discovery, retrogression analysis, and bracket. Impact the position and exposure of the spaces, in which the number of confines is further than the number of samples. Because SVM solves the convex optimization issue analytically, it always returns the same ideal hyperplane value, with exception of evolutionary calculation(GAs) or classifiers, both of which are frequently employed for categorization in deep literacy. The initialization and termination norms play a significant part in perceptron results. While training produces precisely defined SVM parameters for a given training set for a specific kernel that converts the information from the input space to the point space, perceptron and GA classifiers are distinct every time training is begun. As GAs and perceptron's are only interested in minimising training error, multiple hyperplanes will be suitable to satisfy these criteria.

2) *Random Forest:*

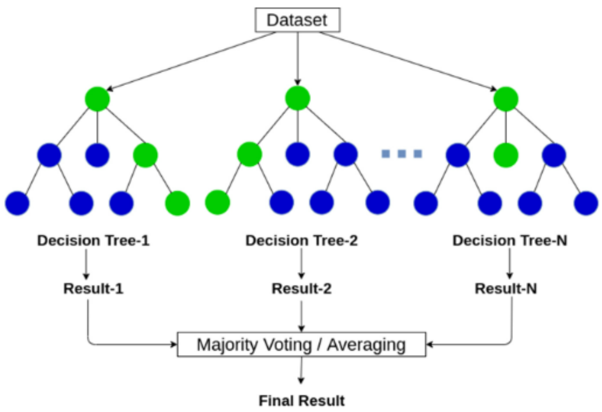

Fig. 3 Random Forest

Leo Breiman and Adle Cutler are the inventors of the widely used machine learning technique known as randomforest, which aggregates the results of various decision trees into a single output. Because to its versatility and usability in handling classification and regression issues, it is widely used. It possesses the characteristic of bagging, which is the softmax classifier's restriction. In most cases, the data set is split into two sets: the train data set and the test data set.Construction of a large number of decision trees is required during the testing period of the random forests or random decision forests ensembles learning method, which can be utilized for categorization, regression, and other tasks. The class that the majority of the trees select is the outcome of the random forest for sorting assignments. The average or median forecast of every individual tree is given for regression problems. Decision trees often overfit their training set, but random choice forests correct this problem.Gradient boosted trees are more precise than random forests, even though they frequently outperform decision trees. Random forests are commonly employed as "blackbox" models in enterprises because they produce excellent predictions across a variety of inputs while requiring little preparation.

3) *Convolutional Neural Network:*

An input layer, hidden layer, and output layer are components of a neural network. While a neuron in the brain continuously analyses and transforms data throughout the body, CNN is inspired by the structure of the human brain. CNN neurons receive information, process it, and then transmit the outcome as output. The output layer transmits the outcome. The image units are stored as input in the input layer as arrays. There may be hidden layers in CNNs that use calculators to extract features from the image.CNN are feed-forward networks, which means that information only moves from their inputs to their outputs in one way. As with ANN, who were biologically motivated.There are numerous variations on the CNN architecture.They often include convolutional and pooling layers for subsampling. There are some that are connected to the neurons or input nodes. They have been tasked with delivering the intended and actual results. When compared, if the actual output differs from the desired result, the existing weights can be changed by giving them new values.

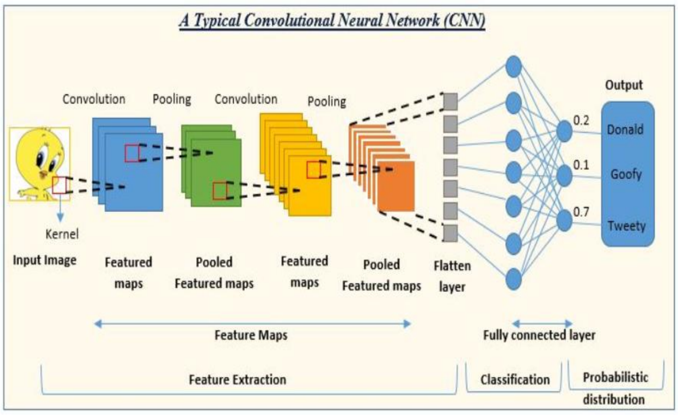

Fig. 4 Convolutional Neural Network

IV. RESULTS AND DISCUSSION

Tasks are typically categorised into broad categories in machine learning. Based on how learning is absorbed or how feedback on learning is provided to the system being developed, several categories have been created. Our methodology consists of seven modules. The modules are follows:

1: Upload Suicide Attempt & Stressed Dataset
2: Preprocess Dataset
3: Machine Translation & Features Extractions
4: Train Propose CNN Algorithm
5: Train Existing Random Forest Algorithm
6: Predict Suicidal Attempt from Test Data
7: Comparison Graph

1. Upload Suicide Attempt & Stressed Dataset

TWINT is used to prepare the dataset before non-depressive data analysis. Combining these two datasets, Text Pattern Recognition can be done. TorchText is used for tokenization.The DAIC-WOZ dataset and the division of audio signals into spectrograms can be used to perform speech pattern recognition. Use the CNN architecture and SVM in combination to find low frequency patterns.The FER-2013 dataset can be used to access facial gesture recognition, and CNN architecture can be used to identify emotions. Split your emotions now into positive and negative ones. Use CNN to detect suicidal intent when dealing with bad emotions.

After taking the dataset from different perspectives, we may observe the following. The dataset's first row provides the names of the dataset's columns, while the other rows contain the dataset's values. In the dataset, there can be some of the values are numeric while others are not, and these non-numeric characters will be converted to numbers using NLP techniques. Each distinct non-numeric character will be given a numeric ID by NLP, and these IDs will be used to train ML algorithms.We will used the dataset to train ML algorithms.After loading the dataset, we can see some records from dataset and dataset contains some non-numeric characters and to translate them we have to pre-process the dataset to remove missing values and then replace with 0.

2. Pre-process Dataset

In below screen we can see all missing data is replaced with 0 and we can see dataset contains total 469 records. In graph we can see total patients with and without suicidal thought. In above graph X-axis represents YES and NO values and y-axis represent total counts of YES and NO patients. YES, means patients has suicidal thoughts and NO means patients has no suicidal thoughts. Now close above graph and then click on ‘Machine Translation & Features Extraction’ button to translate all dataset NON-NUMERIC features to NUMERIC features.

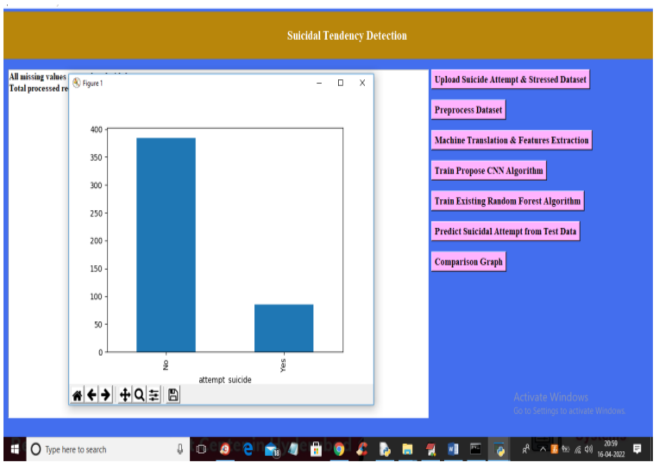

Fig. 5 Pre-process Dataset

After this, we can see complete dataset is translated to numeric data and in below two lines we can see dataset using 614 records to train CNN algorithms and using 154 records for testing CNN performance. Now train and test data is ready and now click on ‘Train Propose CNNAlgorithm’ button to train CNN with above dataset and to get below output.

3. Train Propose CNN and Existing Random Forest Algorithms

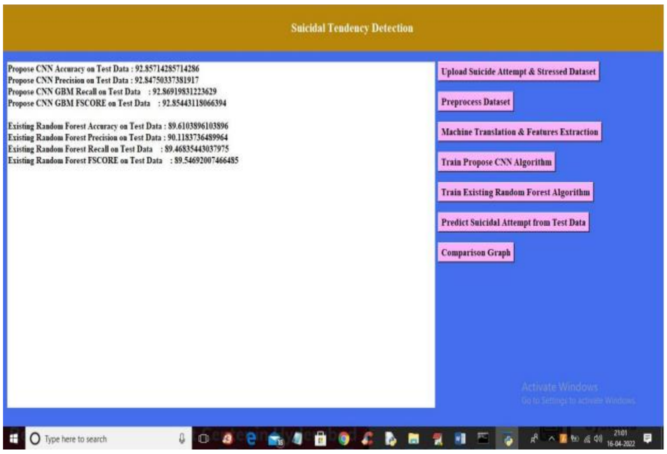

Fig. 6 Accuracies of the Algorithms

In above screen we can see with CNN we got 92% accuracy and now after clicking on 'Train Existing Random Forest Algorithm' button to train existing Random Forest algorithm on same data and calculate accuracy. In above screen with existing random forest algorithm, we got 89% accuracy and now click on 'Predict Suicidal Attempt from Test Data' button to upload test data and then CNN will predict whether test patient records have any suicidal and NO suicidal thoughts.

4. *Comparison Graph*

After training the algorithms, we can see the difference in the accuracies. We can easily plot the graph between those two algorithms according to it.

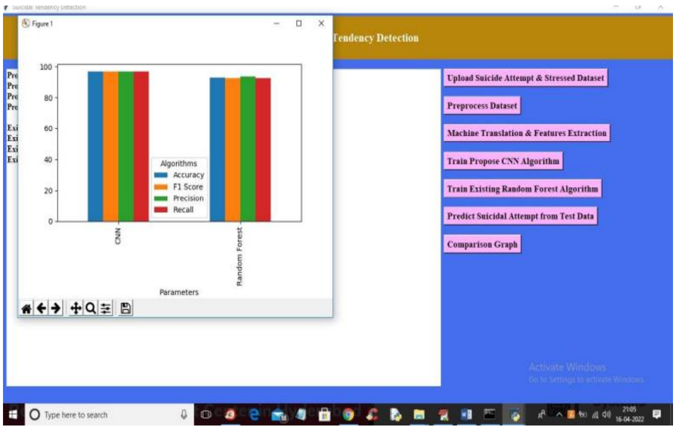

Fig.7 Comparison Graph

In above graph x-axis represents algorithm names and y-axis represents accuracy, precision, recall and FSCORE in different colour bars. In above graph we can see CNN is performing well compare to existing Random Forest algorithm.

V. CONCLUSION

An innovative technique using machine learning is proposed for detecting hanging attempts. After training the system it recognizes the hanging attempts.Using this technique better accuracy and higher sensitivity are obtained on a dataset with substantial variations between different simulated hanging sequences. After training the system it recognizes the hanging attempts. In future, the focus will be more on enhancing the proposed method to increases the chances of detecting the hanging attempts quickly thereby preventing the suicide attempts. By combining the images captured through surveillance camera and the depth information an intriguing path is used to demonstrate the connection between the hanging person and the strangling object. It captures the actions through a camera, generates an alert message.By this, we can easily prevent the hanging attempts. We can successfully propose a method for alarming system.

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