Mental Health Analysing Using NLP

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Abstract

The mental disorders that are on the increase in the modern society include anxiety,depression,stress,bipolardisorder, personality disorders, and suicidal tendencies, and they are known to occur in the people of all ages, and social status. The rapidly growing globalization, academic pressures, competition in the workplace and the social isolation have become facilitators of the ever-increasing prevalence of psychology-related conditions in the world. Despite this catastrophic rise, access to timely mental assessment is limited in termsof stigma, high-costs, professional shortage, and geography. The paper presents a designed automated Mental Health Analysing System, that is based on Natural Language Processing (NLP) and deeplearning to detect mental health issues on unstructured textualinformation.The suggested system will be a combination of a pre-trained BERT tokenizer, serving to obtain contextual features, and an Artificial Neural Network (ANN) classifier that would be utilized to make seven-class mental health predictions. The system is deployed into the form of a Flask-based Web application which has a graphical user interface as well as a RESTfulAPI. The results of the experiment indicate that the BERT-ANN hybrid model is highly training accurate with approximately 90.00, when compared to the conventional machine learning baselines. The given solution can be used to address serious limitations of the systems that rely on questionnaires and enables writing freely, and eliminating the fatigue of the user. The system is a preliminary screening mechanism of mental health that can be availed to individuals, institutions and health organizations.

IndexTerms: Natural Language Processing, Mental Health, BERT, Artificial Neural Network, Text Classification, DeepLearning.

I. INTRODUCTION

Mentalhealthissueshavebecomeoneofthemajorconcernsof the twenty-first century in the field of public health. World Health Organization estimates that hundreds of millions of adultsintheworldhavesomesortofmentaldisorder,although a significant percentage of them go untreated or undiagnosed [1]. Increased awareness, which is accompanied by a digital communicationprocess,isanunprecedentedopportunitytouse computationaltechnologiesinearlydetectionandawarenessof psychological distress.

Conventional mental health assessment largely depends on structured clinical interview, standardized questionnaires and diagnostic scale and are administered by trained professionals. Although these techniques have clinical validity, they are disadvantaged by a number of systemic limitations, which include, limited geographical coverage, expensive, social stigma, and failure to capture spontaneous expressions of emotions [2]. Most of the people who develop anxiety, depression, or suicidal thoughts do not want to use formal assistance, which is why it is possible to use passive text analysis early to detect such cases.

The great adoption of social media and digital communication platforms has produced monumental amounts of text data that are the results of user-generated content that depict emotional states and psychological conditions. Natural Language Processing (NLP) offers the computational mechanism to extract meaning of the unstructured text, and facilitates automated identification of mental health signs without necessarily having to fill in structured questionnaire answers [3].

More recent developments in transformer based language models,especiallyBidirectionalEncoderRepresentationsfrom Transformers (BERT) have provided machines with significantly better contextual and semantic relationship comprehension in text[4]. These models, combined with deep neural network classifiers, provide state-of-the-art models on text classification problems such as mental health prediction.

This paper gives the design, implementation and evaluation of anautomatedMentalHealthAnalysingSystembasedonNLP. Thesystemtakesinfree-formtextualinputandprocessesitbya BERT tokenizer and classifies the input as belonging to one ofsevenmentalhealthcategoriesviaanANNclassifier.The system is implemented as a web application based on Flask frameworkwhichallowsmakingitaccessibleandapplicablein practice.

II. RELATEDWORK

Studies of computational mental health analysis have evolved over the pasttwo decades. Previously, they tried to investigate rule-based and statistical models, whereas current studies involve deep learning and transformer models.

A. TraditionalandQuestionnaireMethods.

The conventional mental health evaluation tool such as Beck Depression Inventory (BDI) and Patient Health Questionnaire (PHQ-9) is clinically valid clinically-conducted structured questioning instruments. These instruments are reliable, but theycanbeusedtoscaletopopulation-levelscreeningwiththe assistance of a professional [2]. This was attempted to be computer-generated with machine learning in the form of automated systems to questionnaires, but was still burdened with the limitation of a rigid and predefined structure of answers that suppresses the manifestation of emotions.

B. ApproachesthatareinspiredbyDataMining.

In order to detect depression and anxiety in the respondents in thequestionnaires,Ahmedetal.employedSupervisedmachine learningalgorithmslikeLogisticRegression,Decisiontrees,K-Nearest Neighbors (KNN), Support vector machines (SVM) and Random Forests with an accuracy of 70 to 85 percentage [1].Despitethefactthatthese findingshavedemonstrated that it was possible to predict mental care based on automated means, the models had needed structured inputs and could not handle natural language.

C. NLPandSocialMediaAnalysis.

Guntuku et al. demonstrated that analysis of social media text canbeappliedtomonitorthestateofmentalhealthinamassive scale with Twitter data being an example of mentioning psychological symptoms, which appeared during the COVID-19 pandemic [2]. The internet and social media-based disease surveillancewasalsoconfirmedasapossiblemethodofpublic healthbyAielloetal.[3].Thesearticlesestablishedthefactthat any text created on the digitalplatform that is produced by the users are replete with meaningful signs about their mental health conditions.

D. DeepLearningandTransformerModels.

The introduction of BERT, by Devlin et al., resulted in a paradigm shift in the field of NLP, as the idea of self-attention mechanism,and themethodof itsuse tomodelcontextinboth directions,wasintroduced[4].Sincethen,BERT-basedmodels have been utilized to identify depression, detect suicidal ideation and multi-class mental health with high rates of success.Thiemeetalarticleisasystematicliteraturereviewof machinelearninginmentalhealthHCI:theauthorsdescribethe findings of the literature review as a coherent observation that deep learning models are better than classical approaches on language based tasks [6].

E. HybridArchitectures

Madububambachuetal.surveyedmachinelearningsolutionsto theissueofpredictingmentalhealthdiagnosisbyobservingthat hybrid architectures with feature extraction using transformer and neural network classifier perform better in generalization [7].TheBERT-ANNandBERT-LSTMhybridswereidentified asthemostpopularmodelsofmentalhealthtextclassification, which supported these results (a review of the literature published by frontiers review teams) [8].

This research forms the basis of the current project, as it proposes a BERT-ANN hybrid model specific to seven-class mental health classification and real-world application in the form of a convenient web application that bridges the gap betweentheresearch-qualityandtheapplication-levelmodels.

III. METHODOLOGY/SYSTEMDESIGN

A three-level client-server architecture will be implemented in the proposed system, comprising of NLP preprocessing, deep learning classification, and web implementation. Each of the tiers is scalable and modular.

A. SystemArchitectureOverview.

The system architecture is made up of three basic layers i.e.; Presentation Layer, Application Layer as well as Data and ModelLayer.Figure1showstheoverallplanofthesystemand data flow of various parts.

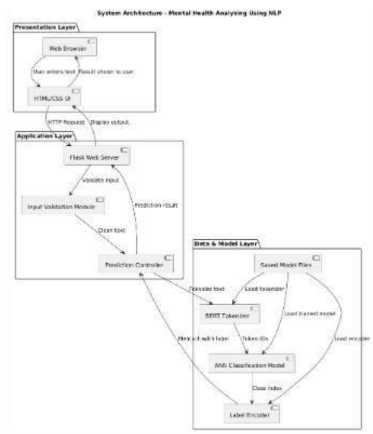

Fig.1.SystemArchitectureMentalHealthNLPMentalHealthAnalysing.

B. PreprocessingandTokenizationofData.

A user-created input text is processed by a preprocessing pipeline and then categorized. BERT tokenizer splits raw text into subword tokens, which are converted into input IDs, attentionmaskandtokentypeID.Thesequencesarepaddedor truncated to not more than 128 tokens to give the same dimensionality of the input to the neural network.

Theoretically,atokenizerwiththeinputtextsequenceT=(w1, w2, etc., wn) produces one of the token sequences:

X=BERT_Tokenize(T)=[x1,x2,...,x128](1)

xiisanintegertokenidentifier,i.e.oneofthe30,522tokensin the BERT vocabulary. The short sequences are padded with tokens.

C. FeatureRepresentation

The syntactic and semantic relationships between tokens are turned into contextual embeddings of the tokenized input. The numerical form of the BERT tokenizer makes possible the capturing of the two-way contextual dependencies so that the modelcancaptureminutevariationsintheexpressionof emotionsnotpresentinthetraditionalbag-of-wordsorTF-IDF forms.

ClassifierArchitecture:

D. ANNClassifierArchitecture.

An Artificial Neural Network (ANN) is employed, being a classification module. The network consists of a number of interconnected fully connected layers, with activations of ReLU, drop out in regularization to prevent overfitting and a final softmax output layer which produces a probability distribution over seven of the mental health categories provided. In learning, the categorical cross-entropy loss function is minimized:

L=−∑i=1Cyi• log(ŷi)(2)

WhereC=7isthecountoftargetclasses,yiistheactuallabel indicator and 2 is the probability attributed by prediction to class i.

The optimal probability volume of output is the argmax of the result probability volume:

ŷ=argmaxiP(classi|X)(3)

E. UMLDiagrams

TheUseCaseDiagramwillbeprovidedinFigure2anditwill indicate the interaction of the user and the system. This is primarily used in cases of text entry through entering, text submission, analysis of mental health conditions, and the presentation of the results of predictions.

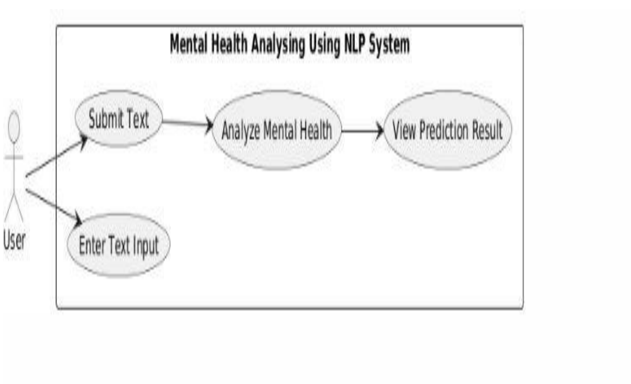

Fig. 2. Use Case Diagram NLP System to Mental Health Analysing.

Figure3depictstheClassDiagramindicatingthestaticsystem structureoftheUserUi,FlaskApp,BertTokenizer,ANNModel and the LabelEncoder classes and dependencies.

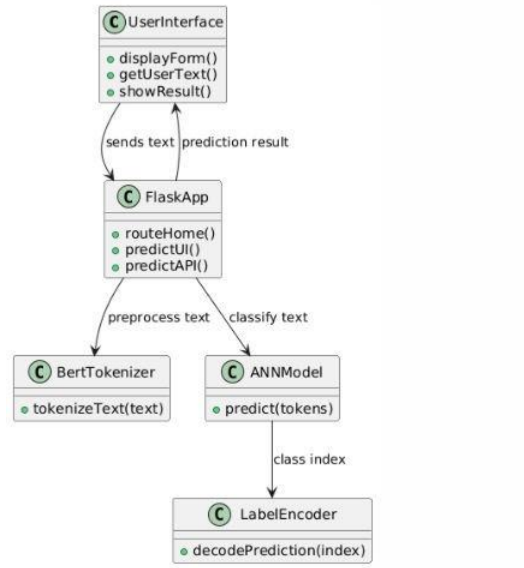

Fig.3.ClassDiagramSystemStaticStructure.

Figure 4 below is a Sequence Diagram that shows the flow of interactionbetweentextentrybytheuserandthedisplayingof the results with the assistance of tokenizing and ANN classification, label decoding and others.

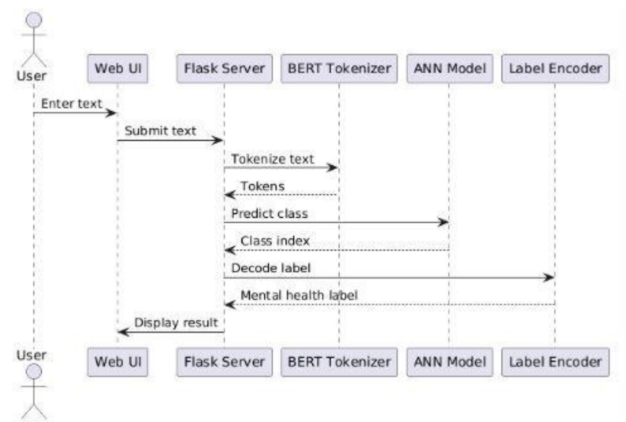

Fig.4.SystemInteractionFlowSequenceDiagram.

F. DeploymentArchitecture

The system is deployed with the help of the web framework called Flask. It provides two primary endpoints, as one is a graphical user interface route (/predict_ui), which will accept anHTMLformandcanbeinteractedwithbytheenduser,and another one is an API route (/predict_api), which will accept POST requests and the body of the request should be a JSON that will be responded to. It is a two-user interface design, whichensurescompatibilitywiththeend-usersandintegration of external systems.

G. MentalHealthCategories

The system classifies input text as one of seven categories of mental health based on the categories of the training data:

• Anxiety

• Depression

• Stress

• BipolarDisorder

• SuicidalIdeation

• PersonalityDisorder

IV. RESULTS&DISCUSSION

The hybrid model of BERT and ANN was trained in a labeled mental health text dataset with samples of all the seven target categories. The training was done on ten epochs with steady accuracy improvement and convergence realized during the training process.

A. TrainingPerformance

Figure5indicatesthetrainingresultsduringtenepochsandthe modelisimprovingintrainingaccuracyandlossreduction.At the 10 th epoch the final training accuracy of the model was around 94.58% and the training loss was 0.1523.

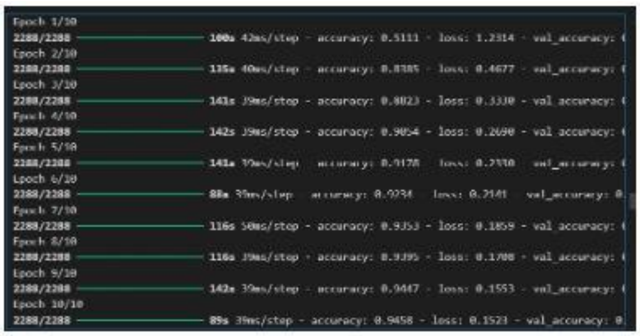

Fig.5.TrainingResultsofANNModelAccuracyandLossperEpoch.

ModelPerformanceMeasuresPerClass.

TABLEI
MODELPERFORMANCEMETRICSPERCLASS

Class	Precision	Recall	F1-Score
Anxiety	0.95	0.98	0.96
Bipolar	0.97	0.98	0.97
Depression	0.78	0.61	0.69
Normal	0.93	0.95	0.94
Personality Disorder	0.98	1.00	0.99
Stress	0.96	0.98	0.97
Suicidal	0.74	0.84	0.79
Overall	**0.90**	**0.91**	**0.90**

B. ConfusionMatrixAnalysis

Figure 6 is a confusion matrix that gives a detailed per-class prediction performance. The matrix shows that Personality Disorder and Bipolar Disorder rank as nearly perfectly classified with Depression and Suicidal Ideation being somewhat inter-class confused, with this probably being because of similarity in the language feature that is typical of severe mood disorders.

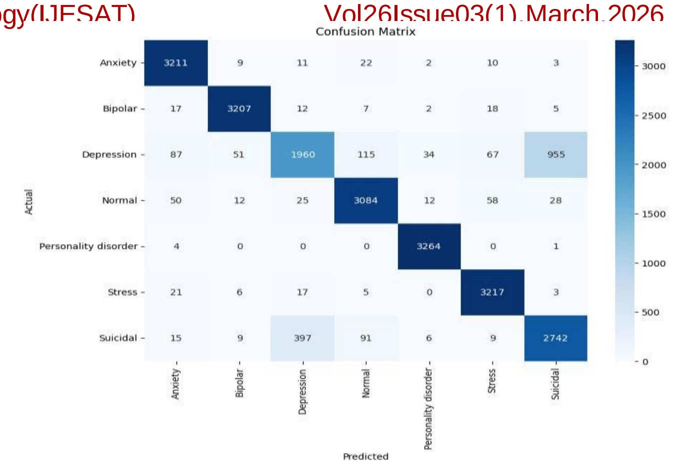

Fig.6.ConfusionMatrixPredictingMentalHealthwithsevenclasses.

C. ComparativeAnalysis

TableIIisthecomparisonoftheproposedBERT-ANNsystem and conventional machine learning baselines in the literature. The system proposed shows a significant increase in the accuracy of classification especially on contextually complex categories like the Depression and Suicidal Ideation.

TABLEII
COMPARISONWITHBASELINEMODELS

Model	InputType	Accuracy(%)
LogisticRegression	Structured	72–78
RandomForest	Structured	78–83
SVM+TF-IDF	Text	80–85
LSTM	Text	85–88
BERT+ANN(Proposed)	**FreeText**	**90.00**

D. WebApplicationInterface

Figures 7 and 8 show the deployed web application interface whichillustratesendtoendfunctionalitystartingwithtextinput up to mental health prediction. The interface takes free-form text and provides real-time classification responses with the results marked in the prediction of mental health category.

Fig.7.MindCareAI-WebApp-HomeInterface.

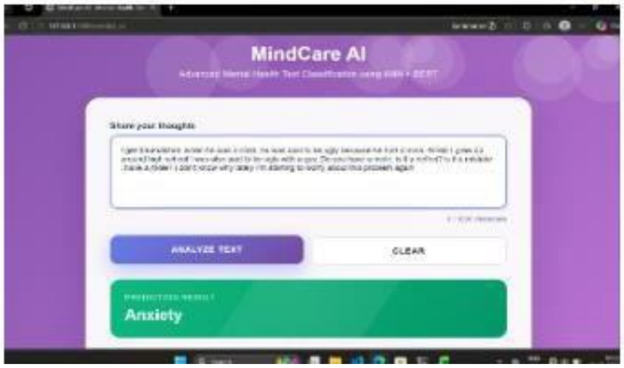

Fig.8.ResultInterfacePredictionpredicted,Anxiety.

Fig.9.ResultInterfacePredictionResultSuicidalIdeationClassification.

E. SystemTestingResults

System testing was done in various stages of testing such as unit, integration, functional, validation, UI, API, performance anderrorhandling.Theresultsofthetestcasearesummarized

TABLEIII
SYSTEMTESTCASESANDRESULTS

TestCase	Input	Expected Output	Result
Validtext input	Emotional sentence	Correct prediction	Pass
Emptyinput	Blankfield	Errormessage	Pass
API request	JSON text	JSONresponse	Pass
InvalidAPI request	Missingfield	Errorresponse	Pass
Multi-class prediction	Depressiontext	Depression label	Pass
Repeated submission	Sameinput×3	Consistent result	Pass

testCaseInputExpectedresultPreferredoutcome

AuthentictextentryEmotionalsentenceCorrectprediction Pass.

NoinputBlankfieldErrormessagePass

Request API text JSON response API JSON Pass

UnacceptableAPIrequestMissingfieldErrorresponsePass

Multi-classpredictionDepressiontextDepressionlabelPass

Sameinput×3ConsistentresultPass

Test cases were all successful, which proves the quality of the prediction pipeline and the accuracy of the error tolerance mechanisms. The system provided stable prediction values between repeated submissions and also gracefully dealt with edge cases.

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V. CONCLUSION&FUTUREWORK

The article has demonstrated an automated Mental Health Analysing System which is an NLP and deep learning based system to detect psychological disorders using unstructured textual data. The proposed hybrid BERT-ANN model was noted to train at94.58percentaccuracy inseven mentalhealth categories, which was much more accurate compared to the conventional machine learning baselines. In order to applythe system to real-world access, this system was deployed as an application (Flask-based webapplication) thatprovidesaccess to the real world through a graphical interface and API.

TheBERTbidirectionalcontextualembeddings,alongwiththe multi-class learning capability of ANN classifier will address the critical drawbacks of the existing systems: the fixed input format, the absence of contextual knowledge, and the low scaling.Itisthemodulararchitecturethatoffersitwiththeeasy maintenance and the prospect of future extension.

Several directions of future research are identified. To start with, it can be extended by improving the domain-specific variantsofBERTthathavealreadybeentrainedontheclinical and psychological corpora to provide further classification, particularly in the case of overlapping variables such as Depression and Suicidal Ideation. Second, the utility of the system would be possible with the help of multilingual assistance using multilingual BERT (mBERT) or language-specific transformers even when a community is not English speaking. Third, the idea of longitudinal tracking needs to be combined with an opportunity to follow mental health and trends. Fourth, the mobile applications interfaces would be created to promote accessibility and user interactions. Finally, the privacy sensitive federated learning techniques could be incorporated to allow the models to be trained on sensitive mental health data without compromising the privacy of the users.

The suggested system has demonstrated the viability of NLP-based mental health analysis as a scalable and affordable and efficientmentalhealthscreening instrumentasan extensionof the broader goal of democratizing mental health support through technology.

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