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Anxiety and Stress Detection through Speech Recognition using CNN

¹C. YOSEPU ¹Associate Professor, ¹Department of Computer Science Engineering, ¹St. Martins Engineering College, Secunderabad, Telangana.

ABSTRACT: Stress is a feeling of emotional tension. It canhaveaninfluenceonourmentalhealth and for the people around us. While anxiety is a natural reaction tostresswhichcanbefearfulthiscanleadtopanicattacks.

These mental issues have to be addressed byeveryone.Thispaperexplainshowweareusingvocal/au diodatasettodetectstressandanxietyinaperson.Wehavede velopedastressandanxietydetection model using deep neural network. Here audio datasets is considered from Kaggle in which the audio consists of 7 emotions i.e., joy, fear, disgust, neutral, sadness, surprised and anger. These audio datasets are used to train and test classification models like CNN. Then the audioispreprocessedthroughacousticfeatureextraction, classified through CNN which provides the accuracy based on those 7emotions. By this wecanpredictif the personisstressedorhasanxiety.

Keyword: [Convolutional Neural Network, Emotion Classification, Stress Detection, MFCC (Mel frequencycepstralcoefficients), Chroma.]

1. INTRODUCTION

Thespeechrecognitionaimstodeterminetheemotionalstat eofanindividualbyusinghis/ hervoice. Speechisameans of communicationtoexpress one"s thoughts and feelings. It is one of the fast and bestways to communicate.

Speechrecognitionismostbeneficialinapplicationsthatre quire human-computer interaction such as speech syn the sis and customer service. Recognizingtheemotional state of an individual using speech signalscanbedifficultforseveralreasons. The speechproce ssing applications has a great influence in ourlife on applications commercial like Text-to-Speechsynthesis, Speechrecognition and verification. Spe echisgivenasaninputtothemachinethataccepts this command. Theinput is translated intotextformatwhichisknownasSpeechRecognition System or Speech to Text. The speech recognitionsystemanalysesanindividualspeechinorderto determine the emotion and produces accurate result. The speech signal which is extracted is trained byDNNmodel.Finally,theoutputobtainedwillbecompare dwithconnectedand continuousspeech.

Emotionsactasanimportantpartineachdayofhuman interactions. Emotions can be happy, fear,sad, anger and disgust. It is necessary to our rationaland intelligent decisions. It helps us to communicateanddeterminethefeelingsofotherpeoplebycomm unicating our feelings and responding to others.Emotionplaysanimportantroleinshapingourbehavior.It displaystheinformationaboutmentalcondition of an individual. The speech signals can beeasily detected by using a microphone. This feature isvery useful for the users and it also helps to maintain, build a large database for stress detection system. Human behavior depends on the way humans act and interact with others. Analyzing human behavior is averyimportantpracticemainlyinpsychotherapy.Behavior can analyzed by observing be the way inwhichemotionchangesduringtheconversation.Here, we implement deep learning in order to analyzetheemotionalstate.Wehavedeterminedtherelationship between emotion and behavior.

furtherusedemotionstoclassifythebehaviorofanindividual. In our system, we take the input speech todetermine speech signals and then predictwhethertheindividualisunderstressor not.

2. RELATEDWORK

researches Stress Recent for detecting and Anxietyhasbeenextremelyprominent.Sometimestheresponse s from Stress allows the body to overcometough situation and prepare for treats but in contrast itcan damage one"s health too. There has been а lot ofdifferentmethodologiesfordetection of Stress and Anxietythroughphysicaltest, questionnaires that primarily rely on user input data which sometimesmay not be accurate or user may find it difficult toanswer some question if it is personal and sometimesmeasuredthrough the speech modulation and

frequencythroughwhichonepersonsayshisthoughtstoothers. In the work done by Maghilnan S, Rajesh KumarM

[1]

workheimplementedSentimentAnalysisbySpeechDatabypro posingfoursteps1) pre-processing which includes VAD. The input signal is givenasaninput to VAD whichidentifiesandsegregate the voice from the signal. The voices arethenstoredaschunksinthedatabase.2)SpeechRecognit ion System. Here the words in the languagespokenbythehumansareconvertedtomachinere adable format which is processed further. The toolsused for speech recognition are Bing speech, GoogleSpeech Recognition. 3) Speaker Recognition Systemwhere the chunks are recognized and each chunks

areidentified and given the Speaker I dithelps in identifying whetherthechunksarefrom the samespeakeror different. The system then matches the Speaker Id with the syste mgeneratedtext. For feature extraction they haveused Mel Frequency Cepstrum Coefficient (MFCC) and for featurematchingtheyhaveused Dynamic Time Wrapping (DTW)4) Sentiment Analysis they have implemented differentalgorithmsuchasNaïveBayes, Linear SVM and VANDER and a comparisonis made to find the efficient algorithm. The accuracyfor Naïve Baves obtained 72.8%. was as Linear SVM86.4% and VANDERas95.2%.

Kevin Tomba, Joel Dumonin , Omar Abou Khaled, Satish Hawalia [2] have discussed about multimodal stress classification system and utilized the aud io/video data to investigate complete number of audio and video features with various fusion techniques a ndtemporal backgrounds for classification purposes. They showed that Teagerenergy cepstral coefficients (TECC) su rpassed standard baseline characteristics in the audiomodal ity, while vector modelling depending on MFCC characteri stics attained the best precision, while on the other hand, polynomial

parameterizationoffaceimagecharacteristicsproducedth edesired output a cross all systems and exceeded the best baseline system. MFCCs are used as features in theextractionmodeltoextractthefeatures. Three differentdatasetswereusedtheBernilemotionaldatabaseR **AVDESS**databaseandKeioUniversityJapaneseEmotion alspeechdatabase.EmoDbandRAVDESSdatabasewerei mplementedusingSVMandKeioSDdatasetusingANN.B othSVMandANNwereoptimized with the help of Scikitlearnlibrarymethod. This method was used infinding the be st combination of values to give the best result for a set of features.SVMandneuralnetworkswereusedintheclassification . Both algorithms showed be stresults, with ANN shavings lightlybetterscoresthanSVMs.Theobtainedresultsperform edgoodclassification and determined if there is stress or not.AndersonR.Avila,ShrutiR.Kshirsagar,AbhishekTiw ari, Daniel Lafond, Douglas O"Shaughnessy and Tiago H.F alk[3]heusedaCNN,SVMandDNNlearningtechniquesan devaluated which modely ields the high estaccuracy. Thise xperimentwasperformedusingSpeechUnderStimulateda ndActualStress(SUSAS)dataset.They proposedtheuse ofmodulationspectralfeatures (MSF) as aninputtoCNNandadoptedOpenSMILEfeaturesandeval uateditwithSVMandDNN.Inordertoextractmodulations pectral features thespeech signalis first normalized to-26dBovandeliminatingunwantedspeechsignals.Thenthe yhavefilteredthesignalsusingkmodulationfilterslaterthef requencies from the filter center are equally spaced from 4 to

requencies from the filter center are equally spaced from 4 to 128 Hz. Finally five features et are extracted. The results sho

wedthattheproposedMSFcombinedwithCNNoutperformedth eothertwolearningmethodsSVMandDNNandgaveanoveralla ccuracy

of 72% while DNN method achieved 62% accuracy and SVM produced 61% accuracy.

Dr.S.Vaikole, S. Mulajkar, A. More, P. Jayaswal, S.Dhas[4]proposedanalgorithmthatfirstextractsMel-

filterbankcoefficientsusingapre-processedspeech data and predicts the stress then output usingCNN.Theaudiosignalispassedtospeechpreprocessingan dthenforwardedtofeatureextraction module. All the necessary speech featuresare extracted and are passed to a deep-learning basedstress detection model. The CNN model determinestheuser"sstressstatebyadecisionprocess.Thepropo sedsystemusesRavdessdatabase.Totalof1440 Speech utterances of twelve male and femalespeakerswere taken. trainingthemodelusingone-hot-Labelswere usedfor encodingapproach. The accuracy was classified into pitchratean dMFCC. Theproposedmodelconsistsof eightCNNlayersand fully connected layers. These layers capture thenecessary information of extracted features and thencalculatetheframeleveloutputeachtime. Theoutput of frame-level is converted into a sentence-levelfeature. The features extracted from layers areof two types that is average value of output sequenceand last frame-level output. The accuracy of stressdetection system using pitch rate was 52% and usingMFCCwas 94.33%. He furtherconcludedthat byusing signal raw energy operator stressed emotionsaredetected with improved accuracy.

Arushi, Roberto Dillon, Ai Ni Teoh [5] proposed aVRbased stress detection model where the speaker"svoice is analyzed on real-time basis where virtuallythe speaker"s speaking skills to the audience will beimprovedbyrealinsightsfromthegamewhichprovides the support/feedback. They have taken thedataset Ryerson Audio-Visual Database of

EmotionalSpeechandSong(RAVDESS).Theyhaveconstructe d 3 classifiers models to extract the voicefeaturesAmplitudeEnvelope(AE),Root-Mean-

Square(RMS)andMel-FrequencyCepstralCoefficients

(MFCCs). Using Random Forest, KNN& SVM training and testing of data is done. MachinelearningAlgorithmslikeGaussianMixtureModel(GM M), Hidden Markov Model (HMM), ArtificialNeural Networks (ANN) and Deep Neural Network(DNN).VRbasedstressdetectionmodelincludesvirtua lenvironment, behaviorof virtual audience, machinelearning mo deldevelopment, feature selection, training and testing of model development. In this model they have kept 70% of data for trainingand 30% for testing the actor"s voice dataset

Thefinalresultsshowsthatrandomforestaccuracyis82%, KNN accuracy is 72% and SVM accuracy 57%,5% and24% accuracy has increasedtodetectthestresswithfeaturesthatincludesRMS,AEa ndMFCC.

3. METHODOLOGY

Dataset Collection

Theactorbasedspeechdatabaseiscomprisedof2768files.Onem

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otionalvalidity,strength,andgenuineness, each filewas scored 10 times. Therewere 24 individuals that were characterized by an untrainedadultstudycandidatesbelongingtoNorthAmerica given scores. High were emotional validitylevels, reliability of interrater, and reliability of testretest interrater were recorded. In the database, thereare 24 trained actors (12 male, 12 female), in a NorthAmericanneutralvoice, clearly expressing two lingu isticallyrelatedphrases.Speechincludesexpressionsofne utral,happy,sad,angry,fear,disgust surprise and calm. emotional At two intensityratios,(strongandnormal),eachexpressionisgen erated with an additional neutral expression. There are three modeformatsavailableforallconditions:audioonly(16bit,48kHz.wav).

Speech Recognition

Speech recognition is the way of converting acoustics(speech of a person) into textual form. This is widelyused in virtual assistants like Rebecca, Siri, Alexa, etc. The google API called Speech Recognition whic h allows us to convert speech into textual forfurtherprocessingbutwhileusingtheSpeechRecogniti on API, translating big or long audio filesinto text, it mav give error messages because it is notthatstrongforlargefilesofaudio.Firstly,weinternally see the input physical audio which will getconverted into electric signals. The electric signals ofour speech signal then gets converted into digitizedform with an analog-to-digital converter. Then, thedigitized model can be used to transcribe the speechinto textualform.

Feature Extraction

Acoustic Features: In general, the more precise andvery basic features of audio to recognize affect areconsidered to be duration, MFCC, energy and pitch. This has been supported by a many researchworkand found it to be themost correct acoustic features to emotions are duration and energy, while all theother features are of medium relevance.

Mel-FrequencyCepstralCoefficients(MFCC)depending on a linear cosine transformation (CT) of alog power spectrum performed on a non-linear Melfrequency scale, it is known as the spectrum of short-term control of an audio or sound. Any type of soundcreatedbyhumansisdefinedbytheirvocaltractshape , including tongue, teeth, lips, etc. The envelopeof the time power spectrum of the audio signal isrepresentative of the vocal tract and MFCC, defined s the coefficients that make up the Melfrequencycepstrumandcorrectlyrepresentthisenvelope. Options are considered for the lower dimensions of the 1st thirteen MFCC coefficients as they represent

thespectraenvelope.Anditsspectraldataisindicatedbythe higherdimensionswhicharediscarded.Envelopesarenece ssaryfordifferentphonemes to display the difference, so we can findphonemesthroughMFCC.Chroma:Itisalso called as

"Chromagram", "Pitchclassprofiles", "Chromafeatures",

that relates to the twelve different kinds ofpitch classes and tuning approximated to the equaltemperedscale. It basically computes melodic and harmonic characteristics of speech or an audio signal. It is consisting of 2 features:

Chroma Vector: It has twelve element expression of spectral energy.

Chromadeviation: It isthetwelve Chromaparametersstandarddeviation.

Convolutional Neural Network

Thedeeplearningmodeldependingupontheconvolutionary neural network (CNN) is used and

itsdenselayershavebeenused.

Astheonlyaudiofeaturetotrainour CNN model, the MFCC and Chroma features are considered the basic approach. The MFC Ccoefficientswereonlyusedfortheirability to reproduce the amplitude spectrum of the audio wave in a compact vector form. As mentioned in, the speech file is split into frames, using a fixedwindowsize.

The discrete Fourier transform is implemented, then the logarithm of the amplitude spectrum is taken into account. After a certain amount of frequency 'Mel'reduction, the spectrumofamplitudeisthennormalized. For a significant reconstruction of the sound wave that can be distinguished by the humanauditoryprocess, this techniqueisperformed to empathize the frequency to a more realistic type. For eachspeechfile, somefeatureswereextracted. Features were produced and along with it converting each speech file to a time series of floating points Then MFCC sequencewascreatedfromthetimeseries.

If the input given is a size < set of training samples >x n x 1onwhich we executed a one-dimensional CNN round as the activation function Re Lu and 2 x2isthemaxpoolingfunction. ReLuasg (z)=max

{0,z},anditgetsalargevalueinthecaseofactivationby

addingthisfunctiontorepresentthehidden units. The last activation layer is used as theSoftmax layer which calculates relative

probabilities.Thenattheendthefullyconnectedlayerisused where the classification happens. Pooling allows theCNN model to focus only on the main characteristics each of the data components, not segregating themby their position. The output of the pooling layer isflattened and this flattened matrix is fed into the fullyconnected layer.

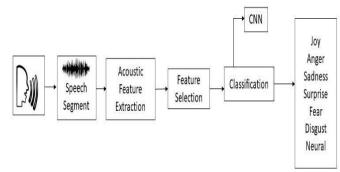


Figure 1: System Overview

4. RESULT

The finding sattained from the evaluation process indicate the effi

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cacyofthemodelonthedatasetrelative to the baselines and the state of the art. Itshows the precision, recall and F1 score values thatwere attained for each of the emotional groups. Thesefindings suggest that recall and accuracy are kind ofbalanced, enabling us to achieve a 0.76 F1 score for the class. The slight shift in F1 highlight stherobustness of the CNN model, which manages 76.08percentaccuracyeffectively.

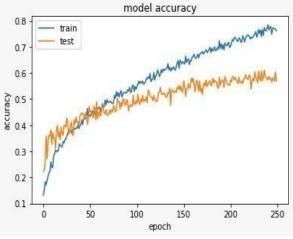


Figure 2: CNN Model Epoch

CONCLUSION

This work presents a deduced model that takes audio as an input and identifies whether the user is under Stress and Anxiety. In this paper we have proposed asimplesystemtocarryouttheabovementionedfunctions. Wehaveextracted the MFCC, MEL and Chromogramfeaturesfromtheaudiofilesusedthroughoutt rainingtoacquiresuchresults.Wetrainedourneuralnetwor kontheaboverepresentations of inputdatatocorrectly figureoutthe probability of distribution of annotation sectionsemploying1-DimensionalCNN,max-

poolingandDense Layers. The result gained can only be worth itas astarting pointforfurtherexpansions,updates,and enhancements.

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