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Emotion Recognition Using Support Vector Machine

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ABSTRACT

Humanemotionsarementalstatesoffeelingsthatarises pontaneouslyratherthanthroughconsciouseffortanda reaccompaniedbyphysiologicalchangesinvoicemusc leswhichimpliesrecognisesonvoice.Someofcriticale motionsarehappy,sad,anger,disgust,fear,surpriseetc. VoiceRecognisesplayakeyroleinnon-verbalcommunicationwhichappearsduetointernalfee lingsof a person that reflects on the voices. In order to computer modelling of human's emotion, a plenty of research has beenaccomplished. But still it is far behind from human vision system.In this paper, we are providing better approach to predicthuman emotions using deep Convolution Neural Network (CNN) ,Support Vector Machine (SVM) and how emotion intensitychangesonavoicefromlowleveltohighlevelo femotion.Thisalgorithmcan beusedindigitalassistantslikeAmazonAlexa ,Google Home to recognise the user emotion and provide services based on their emotional state. The assessments through theproposedexperimentconfersquitegoodresultsando btainaccuracymaygiveencouragementtotheresearch ersforfuturemodelofcomputerbased emotion recognition system.

Keywords:CNN;SVM;HMM;Tkinter;HumanCom puterInteraction;Scikit-Learn,

I. INTRODUCTION

Emotionrecognition is an important element inhuman-computerinteraction,whereemotionrecognition makes this process far more natural. Inemotionrecognitionthephysiologicalstateofaperso n is usually examined,i.e.phenomena suchas changes in body temperature, s k i n r e s i s t a nce(GSR),changesinelectrocardiographic signal (ECG) or blood pressure. However, the easiestsignalstoacquirearethosethatareobservedinco mmunication between people –the human voiceand voicesound.

Theaimofourprojectistoidentify6basicemotions. They are joy, anger, sadness, disgust, fearand astonishment. Its main stages are: recognition ofthearea oftone inthe voice.

HMM-
InHMMBasedClassificationmodel,valuesareemitte dby eachhiddenlayers,andthewhole model generates the sequence of values thatconstitutesthetweet'sfeaturevector.Statesarecons idered to be a set of value that represents the bestemotionalcategories.

CNN- The CNN are made of neurons that havelearnable weights and biases. The neurons on eachlayer perform dot product. The layers in CNN are asequence of layers with input conv, Relu pool, andfully connected layer. Through differentiable functioneachlayertransformsonevolumeofactivation toanother.Thewholenetworkrepresentstheinformati onwithasingledifferentiablescorefunctionfrom converting raw information to a class on the otherside.

SVM- The sum algorithm is to find hyperplane inn-dimensionalspace(N—thenumberoffeatures)thatdistinctlyclassifiesthe data point.

SVM can be used for classification or regressionproblem.Kernel trick is used to transform your data ,then based on these transformation it finds an optimalboundarybetweenthepossibleoutput.

II. EXISTING SYSTEM

Voice recognise plays an important role in non-verbalcommunicationbetweenpeople.Diverseclassif ication of voice recognises might be used innumerousapplicationslike;HumanBehaviourPredi ctor,SurveillanceSystemandMedicalRehabilitatio n.Sevenelementarycategoriesofhuman emotions are

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unanimously predictable acrossdifferentculturesandbynumerouspeopleare:anger, disgust, fear, happiness, sadness, surpriseand neutral. Numerous scholars have used dissimilarmethodsforclassifyingvoicerecognise.Identicalbilateralamygdalaimpairment recognition ofvoice emotions, holistic template-matching to detectrecognise and geometric feature-based approach , theActiveshapemodels:Assessmentofamulti-resolution method , sound preprocessing methods anddescriptorsbasedlocalbinarypatterns,HiddenMarkov Model for recognise detection, Many Hybridapproaches also has been hosted which are like viewbasedModularEigenspacesandahybridapproach ofNNand HMMforvoiceemotionclassification.

1.1. Disadvantage:
Theexistingsystemhasthedisadvantagesare
- Accuracyislowwhencomparedtonewtechnique.
- Italsorequiressomecomputationaldevices.
- Implementationcostishigh.

III. PROBLEM STATEMENT

In the case of emotion classification from the voicesound, the common approach is to train the classifierbasedonthedatacollectedfromvoicesounds, thatarealso involved in testing process. We decided to testclassifiers using voices other than these, used in thetrainingprocess.Itismoredifficult,butmorepracticalfromthepointofviewofthefutureuser.Theclassifierofnearestneighbours(k-NN)doesnotrequirelearning.Dataclassification in this caseisbasedonlyontheproperanalysisoftrainingset.SupportVectorMachine(SVM)focusesonconstructing a hyperplane in a multidimensional spacethatwillbeabletoseparatecasesbelongingtodifferentclasses.

IV. PROPOSED SYSTEM

Themainaimofourproposedschemeistofind outthe standardized parentages of several emotional states(happiness sadness, disgust, anger, surprise, and fear)inavoice.Theemotionhavingthemaximumparentages is projected as its resulting emotion on aspecified voice. Likewise, founded on experimentaloutcomes,trainingandexaminationofvariousemotional phases (frame by frame) has also inspiredus to develop a real-time voice recognize recognitionsystem.Toattainsuchcompositeclassificationoftones, an enormous and robust training is essential.Hence, in this proposed technique concepts of deeplearning using convolution neural networks has beenapplied to train and test the system. The performanceofaneuralnetworkmainlydependsonnumerousissues like initial random weights, training data, andnumberofhiddenlayerandnetworkstructureofsystems.Theconvolutionalneuralnetworksusetones directlyasinput.Asasubstituteofhandcraftedintermediatefeatures,convolutionalneuralnetworks areusedtomechanicallylearnapeckingorderoffeatureswhichcanfurtherbeusedforclassification.

Datasarelinearlyseparableusingsvm.

1.2. Advantages:
The proposed system has the following advantagesare
- Accuracyishigh.
- Highcomputationalprocessing.
- Independentofethnicity.

V. PROPOSED ARCHITECTURE

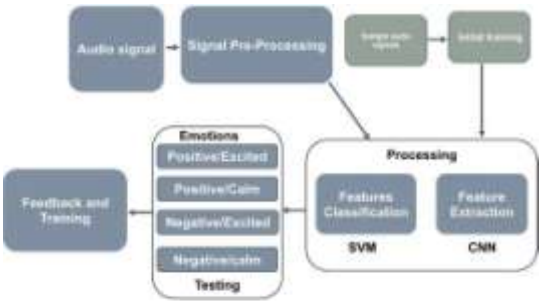

Fig.1.SystemArchitecture

Theproposedsystemissplicedintofollowingmodules

- ➢ UserGUI
- ➢ InitialTraining
- ➢ SignalPreProcessing
- ➢ CNNFeatureExtraction
- ➢ SVMFeatureClassification

1.3. UserGUI

Tkinteris thestandardGUI library forPython.Python when combined with Tkinter provides a fastandeasywaytocreateGUIapplications.Tkinterprovides a powerful object- oriented intervoice to theTkGUItoolkit.

User voice is recorded using the pyaudio library inpython.

User emotion state is displayed after classification .Userfeedbackisusedtotrainthesystemandimprovetheefficiency

1.4. SignalPreProcessing:

Based on the user profile the audio is categorisedand stored to the users model. Features such as Pitch,Tone,Volume,wordGap,WordGaplengthareextractedusingthepythonlibrarysuchaspython_speech_features,pyAudioAnalysis,Pydub.

1.5. CNNFeatureExtraction :

AConvolutionalNeuralNetwork(CNN)iscomprised of one or more convolutional layers (oftenwith a subsampling step) and then followed by one ormorefullyconnectedlayersasinastandardmultilayer neural network.

TimeSeriesPredictionwithLSTMRecurrentNeural Networks in Python with Keras. The LongShort-Term Memory network or LSTM network is atypeofrecurrentneuralnetworkusedindeeplearningbecause very large architectures can be successfullytrained.

1.6. SVMFeatureClassification:

Scikit-learn is a free machine learning library forPython.Itfeatures various algorithmslikesupportvector machine, random forests, and k- neighbours,and it also supports Python numerical and scientificlibrarieslike NumPyandSciPy.

ThelinearSVMclassifierworksbydrawingastraight line between two classes. This is where theLSVMalgorithm is used.

VI. CONCLUSION

In this paper, A system, which enabled extractionofgeometricalandanthropometricfeaturesfromsoundsofvoices,wascreated.Onthisbasis,comparison of the operation of various classifiers, intheimplementationofthetaskofemotionrecognition ,was performed. The support vector machine (SVM).We achieved averaged classification accuracy 57.7%for 5 different emotions (angry, excited, sad, normalandnervous)andaverageclassificationaccuracy95.9%for 2emotions(excited,sad).

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