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Performance Analysis of Machine Learning Algorithms for Gender Classification

Laxmi Narayana Pondhu
Department of Computer Science and Engineering
Rajiv Gandhi University of Knowledge Technologies
Basar, India
laxmi916@gmail.com

Govardhani Kummari
Department of Computer Science and Engineering
Kodada Institute of Technology and Science for Women
Kodada, India
k.govardhani@gmail.com

***Abstract*—We have various machine algorithms for gender classification but choosing best one is important task. For selecting best algorithm we conducted experimental study on machine learning algorithms for gender classification. In this experimental study of machine learning algorithms, we analyzed performance of various algorithms for gender classification using voice dataset. From this study we concluded that SVM and ANN are giving best results. After tuning parameters ANN outperforms SVM giving accuracy 99.87% on test data.**

Keywords—Machine learning; Deep learning; SVM; Artificial Neural Networks;

I. INTRODUCTION

Gender prediction is important in applications like targeted advertisements, interactive systems and mobile based health care systems. Based on the gender of a person interactive systems respond accordingly. If marketing firms know the the gender of the person then they can target respective people who potentially buy the products. Classifying the gender of a person accurately based on their voice is a challenging problem in machine learning.

Deep learning models are more suitable for unstructured data like audio, video and images. Deep learning models perform better results when the data is large.

In this paper we used the voice dataset consists of 3168 male and female voice acoustic features to train different machine learning algorithms. From this research we compared the accuracy of different algorithms.

II. RELATED WORK

There are numerous machine learning, deep learning models to classify the person is male or female based on speech. In [1] with Support Vector Machines attained 95% accuracy for the gender classification system. In [2], pitch was used for the gender classification with Multi Layer Perception Neural networks chived the accuracy of 96%. In [3] Support Vector Machines, Classification and Regression Tree (CART) [4] models were used. In [5] Lee and Lang used Support Vector Machine(SVM). In [6] Silvosky and Nouza used Gaussian Mixture Models(GMM). In [7] by using Multilayer Perceptron (MLP) networks achived 96.74% accuracy.

III. SPEECH DATASET

The speech dataset [10] has 3168 voice samples of male and female. Each sample consists acoustic properties of voice.

Dataset file contains the following fields [9]:

meanfreq, mode, sd, centroid, Q25, Q75, skew, IQR, kurt, sp.ent, meanfun, minfun,maxfu, mindom, meandom, maxdom, dfrange, modindex,label.

“label” two values for male or female classification.

The remaining fields are acoustic properties of voice dataset described in TABLE I.

TABLE I. ACOUSTIC PROPERTIES OF EACH VOICE SAMPLE

Acoustic Properties	
Properties	***Description***
meanfreq	mean frequency (in kHz)
sd	standard deviation of frequency
median	median frequency (in kHz)
Q25	first quantile (in kHz)
Q75	third quantile (in kHz)
IQR	interquantile range (in kHz)
skew	skewness (see note in specprop description)
kurt	kurtosis (see note in specprop description)
sp.ent	spectral entropy
sfm	spectral flatness
mode	mode frequency
centroid	frequency centroid
peakf	peak frequency (frequency with highest energy)
meanfun	average of fundamental frequency measured across acoustic signal
minfun	minimum fundamental frequency measured across acoustic signal

maxfun	maximum fundamental frequency measured across acoustic signal
meandom	average of dominant frequency measured across acoustic signal
mindom	minimum of dominant frequency measured across acoustic signal
maxdom	maximum of dominant frequency measured across acoustic signal
dfrange	range of dominant frequency measured across acoustic signal
modindx	modulation index. Calculated as the accumulated absolute difference between adjacent measurements of fundamental frequencies divided by the frequency range
label	male or female

IV. Performance Analysys of Algorithms

Classification algorithms are used for solving problems like identification of person gender, intruder detection and Spam detection etc. In this research paper we compared classification algorithms using voice dataset.

We did conduct experiment with machine learning classification algorithms on voice dataset and observed the train and test set accuracies for seven classification algorithms.

We used sklearn preprocessing library for data preprocessing. In voice dataset no missing values present in the dataset, label-encoder used for converting string values into int values and applied standard scalar for standardization of values . We used pandas, numpy packages to load the dataset, to perform numerical calculations respectively and sklearn package used for modeling the machine learning algorithm. In all the experiments test set size is 0.25. Keras and Tensorflow used in Artificial Nural Networks(ANN). We used 10 fold cross validation to train the models. The accuracies are shown in the Table II.

Both the SVM and ANN are giving better results compared with other machine learning algorithms. SVM is giving 97% accuracy on both train, test sets with linear kernel. Artificial Neural Network with three hidden dense layer of each contains 1000 nodes and relu as activation function, one input layer with 20 features and one output layer consists two nodes. In the output layer softmax is used as activation function and adam optimizer used then ANN is giving 98% accuracy.

From the TABLE II we can conclude SVM and ANN have better accuracies. Parameters influences the machine learning algorithm performance. We can further improve these algorithms by parameter tuning.

TABLE II. Accuracy of Machine Learning Models

Accuracy(%)		
Model	***Training set***	***Test set***
Logistic Regression	97.264	97.727
KNN	98.527	97.727
Naive Bayes	89.352	89.394
Decision Tree	100	96.717
Random Forest	99.832	97.601
SVM	97.432	97.97
ANN	100	98.358

V. Praposed Work

Parameter tuning [11] is used to find the best hyper parameters. GridSearch technique is used to find best hyper parameters. GridSearch will test several combinations of hyper parameters and returns the best selection that gives best accuracy.

We created dictionary with hyper parameters and applied on GridSearchCV of karas library. GridSeachCV will train Artificial Neural Networks using k-fold cross validation to get relevant accuracy with different combinations of the dictionary of hyper parameters and returns best accuracy with best selection of these values.

We tried with several hyper parameter on ANN algorithm with different batch sizes 10,20,32, different number of epochs 50,100,200 and with different optimizers are adam, rmsprop. Best parameter values are batch size 32, epochs 100 and optimizer rmsprop.

We applied parameter tuning on SVM using GridSeachCV with different kernels linear, rbf, poly, different gamma and C vales. Best parameter values are C 0.6, gamma 0.04 and kernal rbf. After applying parameter tuning SVM, ANN are giving improved results. We applied 0.1 dropout between hidden layer to avoid over fitting machine learning model.

VI. Result Analysis

The improved accuracies of SVM, ANN are shown in the Table III.

TABLE III. Accuracy of Models after Parameter Tuning

Accuracy(%)		
Model	***Training set***	***Test set***
SVM(kernel='rbf')	98.274411	98.611111
ANN	99.789562	99.873737

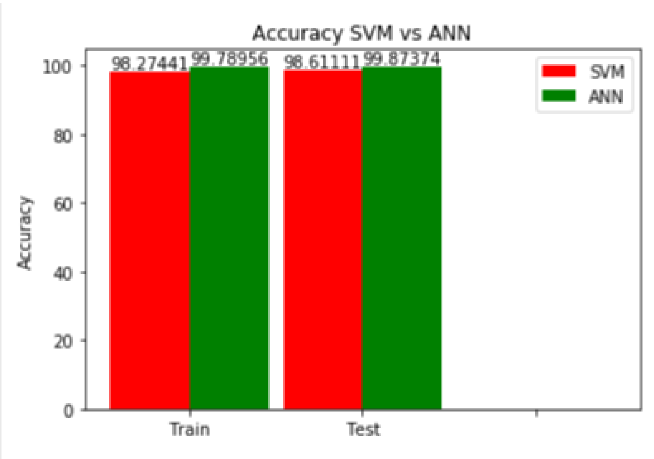

Fig. 1. Accuracy SVM vs ANN.

Results of algorithms are shown in the Fig. 1. X-axis shows algorithms and Y-axis shows Accuracy of the algorithm.

VII. CONCLUSION

Support-vector machines and Deep neural networks are performing better on voice dataset. Parameter Tuning is giving the 98.6% accuracy with SVM and 99.87% with ANN. From the above results we can conclude that deep neural networks are performing better compared with all machine learning algorithms to classify gender of a person using acoustic properties of voice.

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