AN ADOPTIVE ARTIFICIAL NEURAL NETWORK FOR GENDER CLASSIFICATION

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Abstract

Machine learning is an application of artificial intelligence (AI) that provides systems the ability to automatically learn and improve from experience without being explicitly programmed. Machine learning focuses on the development of computer programs that can access data and use it learn for themselves. We have different machine calculations for sexual orientation characterization however picking best one is critical undertaking. For choosing best calculation we led exploratory investigation on AI calculations for sexual orientation order. In this exploratory investigation of AI calculations, we analyzed performance of different calculations for gender orientation arrangement utilizing voice dataset. From this examination we inferred that SVM and ANN are giving best outcomes. In the wake of tuning parameters ANN beats SVM giving exactness 99.87% on test information.

Keywords: *Machine Learning, Support Vector Classifier, Artificial Neural Networks, Deep Learning.*

I. INTRODUCTION

Machine Learning is a subset of AI. That is, all AI considers AI, however not all AI considers AI. For instance, emblematic rationale – rules motors, master frameworks and information charts – could all be portrayed as AI, and none of them are AI.

One angle that isolates AI from the learning diagrams and master frameworks is its capacity to adjust itself when presented to more information; for example AI is dynamic and does not require human mediation to roll out specific improvements. That makes it less fragile, and less dependent on human specialists. Profound learning is a subset of AI. More often than not, when individuals utilize the term profound learning, they are alluding to profound fake neural systems, and to some degree less regularly to profound fortification learning.

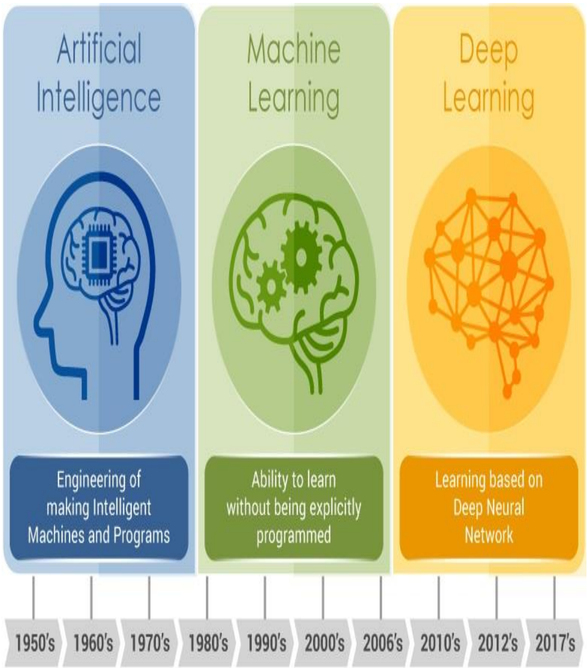
Artificial neural systems are a lot of calculations that have set new records in exactness for some essential issues, for example, picture acknowledgment, sound acknowledgment, recommender frameworks, and so on. For instance, profound learning is a piece of Deep Mind's outstanding AlphaGo calculation, which beat the previous best on the planet Lee Sedol at Go in mid 2016, and the present title holder Ke Jie in mid 2017.Gender orientation forecast is essential in applications like focused on promotions, intelligent frameworks and versatile based social insurance frameworks. In view of the sexual orientation of an individual intelligent frameworks react as needs be. In the event that showcasing firms know the sexual orientation of the individual, at that point they can target separate individuals who possibly purchase the items. Characterizing the sexual orientation of an individual precisely dependent on their voice is a testing issue in AI. Profound learning models are progressively appropriate for unstructured information like sound, video and pictures. Profound learning models perform better outcomes when the information is huge. In this paper we utilized the voice dataset comprises of 3168 male and female voice acoustic highlights to prepare diverse AI calculations. From this exploration we looked at the exactness of various calculations.

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.



EXISTING SYSTEM

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. Classifying the gender of a person accurately based on their voice is a challenging problem in machine learning.

III PROPOSED SYSTEM

Parameter tuning 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 GridSearch CV of keras 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. 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 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. 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.

IV METHODOLOGY

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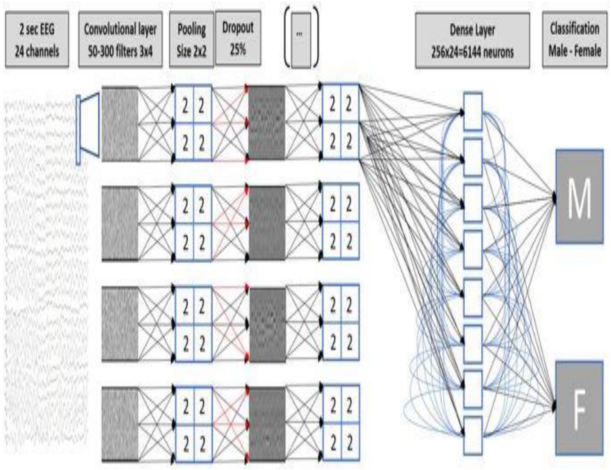

Fig: ANN for Classification of Gender

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 kernel 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.

V CONCLUSION

In this paper, we defined features of phishing attack and we proposed a classification model in order to classification of the phishing attacks. This method consists of feature extraction from websites and classification section. In the feature extraction, we have clearly defined rules of phishing feature extraction and these rules have been used for obtaining features. In order to classification of these feature, SVM, NB and ELM were used. In the ELM, 6 different activation functions were used and ELM achieved highest accuracy score.

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