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A Machine Learning Ensemble Classification Approach for MIMO-OFDM

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Abstract: ***In the early days recognition of the errors in transmissions may diminish the time postponement of communications. The customary error recognition methods are not exact adequate. A machine learning based methodology is proposed to take care of this issue because of the ongoing momentous advancement. The machine learning technique acquires the transmission state is thought to be a component of the highlights of a channel situation like the impedance and the noise. The preparation dataset is produced by reproductions on the channel condition. The ensemble machine learning algorithms are namely AdaBoostM1, Attribute Selected Classifier, Bagging, Classification via Regression, and Random Committee implemented in this research work and found the best algorithm for giving best accuracy.***

Index Terms: ***Bagging, MIMO, AdaBoostM1 , OFDM, and RandomCommittee.***

I. INTRODUCTION

The last two decades, the utilization of remote correspondence has surpassed the utilization of individual correspondence or human-to-human (H2H) correspondence. Along these lines, we have to accomplish high unearthly proficiency, refresh client encounter and decrease idleness in this broadly utilized remote correspondence. These days, the data network for the machine-to-machine (M2M) gadgets is set under popularity, which plays a main consideration in the cutting edge [1]. Another sort of traffic that has landed in the cell correspondence framework by interconnecting the substantial gadgets is known as the Internet-of-Things (IoT) [2]. The usage of gigabit ethernet (GigE), Internet of Things (IoT), vision web and heterogeneous systems (Hetnets) has been helped by the fifth generation systems [3]. Of these, the IoT innovation upheld by M2M has modernized applications, including agribusiness, transportation, following, metering, e-wellbeing, etc. A portion of the plan viewpoints identified with enormous M2M foundations incorporate the numerous entrance framework [4], sharing of the assets and the diverse parts of systems administration [5]. Multi-user detection (MUD) is a recipient innovation committed to the discovery of all the meddling signs by means of compressive sensing (CS) [6]. In the event that more gadgets are not in a functioning state (client action is low), the transmitting signal vector has a meager property because of an extensive number of non-zero components. Subsequently, the interpreting of the transmitted flag turns into a CS issue [7]. The long haul development is fitting for a framework that gives few high actions of clients. Be that as it may, these movements for machine-type correspondence (MTC) where a higher number of clients with less action sporadically sends few bundles [8].

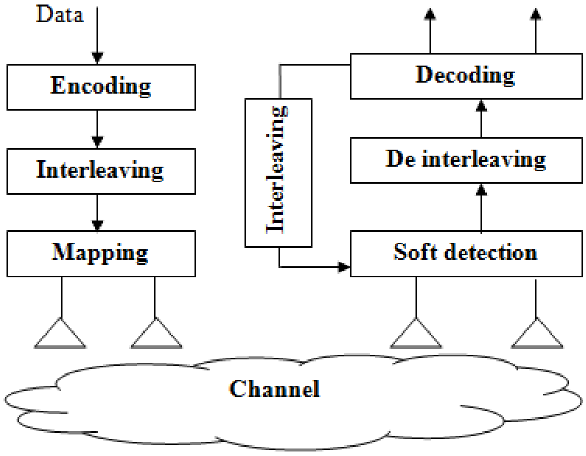

Fig.1 Block diagram of MIMO-OFDM

In this paper organizes section one has related works and brief introduction of this fields, section two presents Materials and Methods, in section three describes results and discussions and the section four presents conclusion.

II. MATERIALS AND METHODS

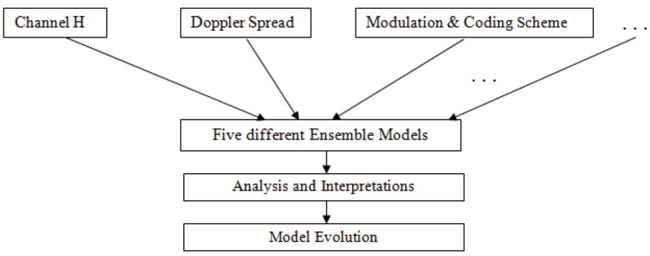

Fig.2 Architecture of Proposed Machine Learning Model

MIMO, Multiple Input Multiple Output, is the key technology used in the 3G/4G wireless system. It provides greater spectral efficiency, better reliability, and larger data rate compared with the traditional Single Input Single Output (SISO) system. The Main agenda of this research work is to offer a framework to classify the transmission states in different communication environments. Orthogonal Frequency Division Multiplexing (OFDM) is a leading wireless broadband technology.

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OFDM operates over a wide range of frequency; therefore naturally the data rate is higher, which is suitable for the 3G/4G system. OFDM has been employed in 4G wireless systems like LTE. In the meantime, OFDM is practical because it has a low complexity of implementation.
The performance of a classifier is measured based on the confusion matrix shown in figure 3, which is built after each prediction made and compared with the real outcome.

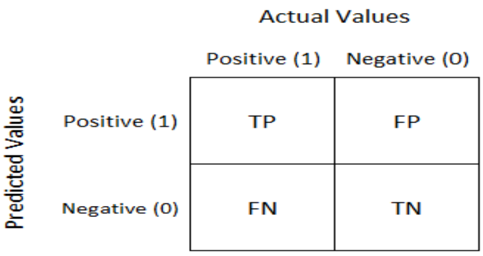

Fig.3 Confusion Matrix

Table 1 Channel Environments

SIMO Configuration	RB Number	Channel H	MCS Value	Doppler Spread
1x2	6 (Corresponding to 2 OFDM Subcarriers)	72X14X2 (72(subcarriers), 14(symbols), 2 (antenna) complex number matrix)	0,5,10,15,20	5,70

The channel H is a 72 X 14 X 2 complex number matrix that is equal to a 4032-dimensional vector, if the real part and imaginary part of the complex number are counted separately. Therefore, the input of the model is a vector more than 4000 dimensions, which is hard to calculate and easy to cause the curse of dimensionality problem. Dimension reduction consists of two parts: feature selection and feature extraction.

Table 2 Dataset Configuration

Name	Size	Channel Type	MCS	Doppler Spread	IOT	RBs	Antennas
EVA	60000	EVA	5	5	20dB	6	2
General	120000	EVA	0,5,10,15,20	5,70	20dB	6	2

Feature selection picks a subset of original features that is based on the prior knowledge from wireless communications. On the other hand, feature extraction transforms the high dimensional data into another space with lower dimensions and the transformation might be linear or non-linear. The most popular linear feature extraction algorithm is Principal Components Analysis (PCA).

The research focuses algorithms are inspired by the popular supervised classification methods that include AdaBoostM1, Attribute Selected Classifier, Bagging, Classification via Regression, and Random Committee in ensemble model. The experiments on these algorithms evaluate the performance of different ML algorithms for the CRC prediction task. The best algorithm can be chosen by comparing the performance.

AdaBoostM1, Attribute Selected Classifier, Bagging, Classification via Regression, and Random Committee were applying in Weka tool for Cross-validation is the evaluation approach for judging the performance of different models and the training and validation dataset split is 90% and 10%, respectively. The general prediction accuracy computed based on the whole validation dataset.

III. RESULTS AND DISCUSSIONS

In this section describes the results and discussions about on this research work. When Principle components has 16 numbers then accuracy level of all five ensemble models have namely AdaBoostM1, Attribute Selected Classifier, Bagging, Classification via Regression, and Random Committee have respectively 98.58%,93.05%,98.42%,92.71% and 98.73%.

Table 3 Accuracy of AdaBoostM1; Attribute Selected Classifier, Bagging, Classification via Regression, and Random Committee Model

No of Principle Components	AdaBoostM1	Attribute Selected Classifier	Bagging	Classification Via Regression	Random Committee
16	98.58 %	93.05 %	98.42 %	92.71 %	98.73 %
32	98.61 %	93.13 %	98.47 %	92.70 %	98.81 %
64	98.49 %	92.75 %	98.43 %	92.70 %	98.89 %
128	99.77 %	93.74 %	98.53 %	92.96 %	98.91 %
256	98.49 %	92.72 %	98.36 %	92.28 %	98.89 %

When Principle components has 32 numbers then accuracy level of all five ensemble models have namely AdaBoostM1, Attribute Selected Classifier, Bagging, Classification via Regression, and Random Committee have respectively 98.61%,93.13%,98.47%,92.70% and 98.81% level of accuracies. When Principle components has 64 numbers then accuracy level of all five ensemble models have namely AdaBoostM1, Attribute Selected Classifier, Bagging, Classification via Regression, and Random Committee have respectively 98.49%,92.75%,98.43%,92.70% and 98.89% level of accuracies.

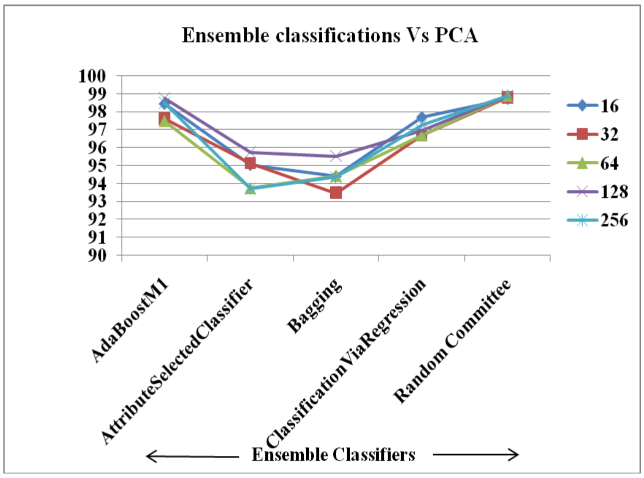

Fig.4 Graphical Representation of Ensemble Models

When Principle components has 128 numbers then accuracy level of all five ensemble models have namely AdaBoostM1, Attribute Selected Classifier, Bagging, Classification via Regression, and Random Committee have respectively 99.77%,93.74%,98.53%,92.96% and 98.91% level of accuracies.

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When Principle components has 258 numbers then accuracy level of all five ensemble models have namely AdaBoostM1, Attribute Selected Classifier, Bagging, Classification via Regression, and Random Committee have respectively 98.49%,92.72%,98.36%,92.28% and 98.89% level of accuracies.

IV. CONCLUSION

In this research work, there are five machine learning ensemble algorithms outperform the calibration method in the EVA dataset, which proves that the machine learning methods work for this problem and can provide higher accuracy. The AdaBoostM1 model has the best prediction accuracy at 128 principle components. However, the AdaBoostM1usually has a lot of parameters depending on the number of layers and the number of nodes in each layer, which requires a long training time. Therefore, the AdaBoostM1model is the best algorithm for this problem and the suitable feature design is to directly use principal components.

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