International Journal of Innovative Technology and Exploring Engineering (IJITEE)
ISSN: 2278-3075 (Online), Volume-8 Issue-4, February 2019

A Novel Classification Approach for MIMO-OFDM

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Abstract*: The expanding unpredictability of designing cellular networks recommends that machine learning (ML) can successfully enhance 5G advances. Machine learning has proven successful a performance that scales with the measure of accessible data. The absence of vast datasets restrains the twist of machine learning applications in remote interchanges. The transmission state is thought to be a component of the highlights of a channel situation like the obstruction and noise, the relative motion between the transmitter and the receiver and this capacity is acquired by the machine learning strategy. The preparation dataset is produced by recreations on the channel condition. The Jrip, J48 and Naïve Bayes are the three algorithms implemented in this research work. This research work test if machine learning methods can predict the transmission states with a high accuracy compared to conventional approaches.

***Index Terms*: Machine Learning, Jrip, MIMO, J48, OFDM, CRC and Naïve Bayes.**

I. INTRODUCTION

Machine learning has been connected to an extensive assortment of issues in media communications in now a day's [1, 2, and 3]. The mapping procedure interfacing join level test systems and framework level test systems is indispensable and has just been considered cautiously in remote correspondence. Normal Value Interface and Actual Value Interface [4] have been utilized to interface the connection level with the framework level. Be that as it may, the two strategies are not exact or sufficiently productive for the basement organizes. As of late, a few connect to-framework mapping strategies have been proposed, which are exact and valuable for high information rate framework by utilizing compelling Signal to Interference in addition to Noise Ratio (SINR). Exponential Effective SINR Mapping (EESM) and Mutual Information based Effective SINR Mapping (MI-ESM) are the two L2S strategies generally actualized in current remote correspondence frameworks.

The blend of machine learning and correspondences frequently alludes to the term psychological radio which was first proposed by Joseph Mitola [5]. A learning engine is proposed to incorporate with a reasoning engine so that can recall the information considered from the past and settle on choices precisely and rapidly later on [6].

With the amazing advancement in computer vision territory accomplished by machine learning calculations, analysts as of late make the starter examinations on the correspondence framework with profound learning systems. A deep learning based methodology for channel unraveling issues with bits of proof demonstrating that neural systems can become familiar with a type of disentangling calculation, as opposed to just a straightforward classifier [7].

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.

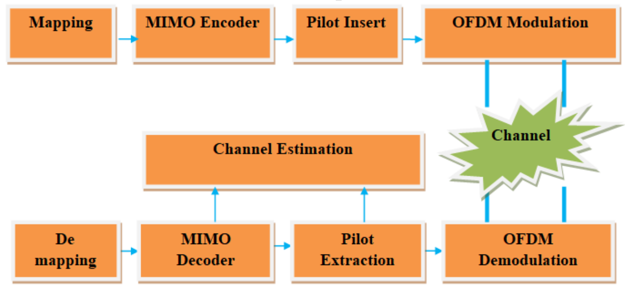

Fig.1 MIMO-OFDM Model

II. MATERIALS AND METHODS

MIMO, Multiple Input Multiple Output, is the key technology used in the 3G/4G wireless system. MIMO using diversity techniques can provide diversity gain that is beneficial for improving the reliability, while applying MIMO using spatial multiplexing techniques provides multiplexing gain that aims to improve the data rate of the system. The goal of this research is to offer a framework to classify the transmission states in different communication environments. Two datasets are used to evaluate the performance of different models. Orthogonal Frequency Division Multiplexing (OFDM) is a leading wireless broadband technology. The term broadband means a wireless system with broad bandwidth.

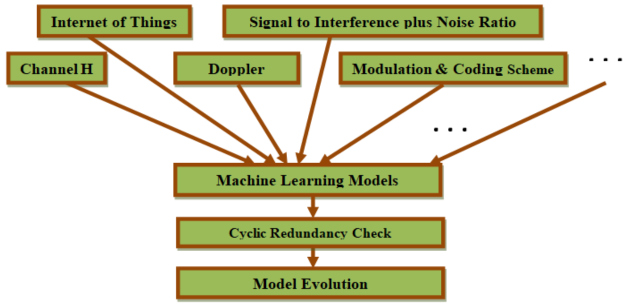

Fig.2 Architecture of Proposed Machine Learning Model

Manuscript published on 28 February 2019.
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The performance of a classifier is measured based on the confusion matrix, which is built after each prediction made and compared with the real outcome. A confusion matrix is a table that is often used to describe the performance of a classification model (or "classifier") on a set of test data for which the true values are known. The confusion matrix itself is relatively simple to understand, but the related terminology can be confusing. The inputs are the features of channel environments and the output is the CRC value which is either 0 or 1.

The channel H is a 72 x 14x 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 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

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 algorithms are Principal Components Analysis (PCA). The research focuses on supervised learning; the selected algorithms are inspired by the popular supervised classification methods that include Jrip in rules, J48 in Decision Tree and Naïve Bayes (NB) in bayes. 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.

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

Jrip: his class implements a propositional rule learner, Repeated Incremental Pruning to Produce Error Reduction (RIPPER).

J48: The C4.5 algorithm for building decision trees is implemented in Weka as a classifier called J48.

NaiveBayes: Class for a Naive Bayes classifier using estimator classes. Numeric estimator precision values are chosen based on analysis of the training data.The NaiveBayesUpdateable classifier will use a default precision of 0.1 for numeric attributes when buildClassifier is called with zero training instances.

Jrip ,J48 and NaiveBayes 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. To standardize the model performance, the performance metric uses two types of accuracy. One is the general prediction accuracy, which is computed based on the whole validation dataset.

III. RESULTS AND DISCUSSIONS

In this section describes the results and discussions about this research work. Two different strategies are analyzed with PCA. The first hypothesis is that it is because the post-SINR is not used in this feature setting.

Table 3 Accuracy of the Jrip, J48 and NaiveBayes applying PCA on the channel H as the input (without using Post-SINR)

No of Principle Components	Jrip		J48		Naïve Bayes	
	General Accuracy	Descending Accuracy	General Accuracy	Descending Accuracy	General Accuracy	Descending Accuracy
16	65.91%	53.13%	66.39%	50.57%	97.66%	92.22%
32	69.49%	54.58%	67.58%	49.39%	97.67%	92.22%
64	71.91%	56.23%	68.07%	49.71%	97.60%	91.99%
128	71.55%	55.99%	69.04%	50.32%	97.71%	92.36%
256	71.64%	55.85%	66.65%	47.84%	97.98%	93.17%

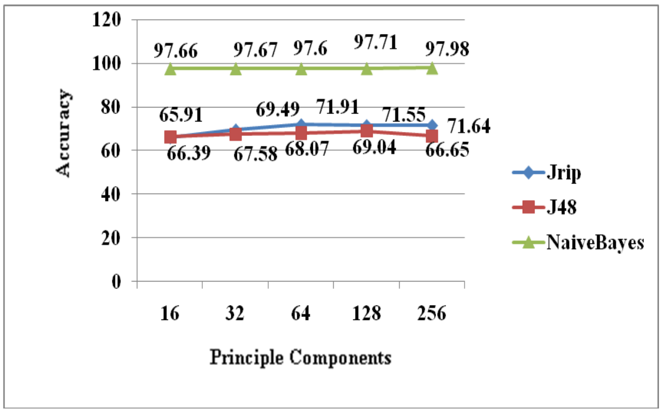

Fig.3 General Accuracy of the Jrip, J48 and Naïve Bayes applying PCA on the channel H as the input (without using Post-SINR)

In the baseline and feature selection strategy, the post-SINR is one of the inputs and both models perform well. Therefore, the post-SINR may be a major factor that affects the model performance.

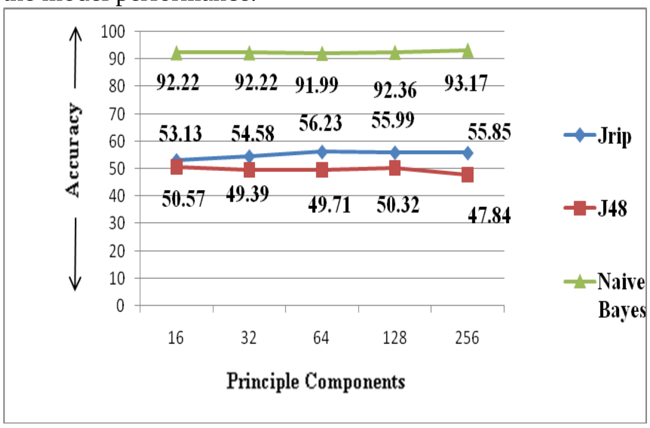

Fig.4 Decreasing Accuracy of the Jrip, J48 and Naïve Bayes applying PCA on the channel H as the input (without using Post-SINR)

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Table 4 Accuracy of the Jrip, J48 and Naïve Bayes model using post-SINR

No of Principle Components	Jrip		J48		Naïve Bayes	
	General Accuracy	Descending Accuracy	General Accuracy	Descending Accuracy	General Accuracy	Descending Accuracy
15	97.58%	92.05%	97.42%	91.71%	97.73%	92.55%
31	97.61%	92.13%	97.47%	91.70%	97.81%	92.86%
63	97.49%	91.75%	97.43%	91.70%	97.89%	91.07%
127	97.77%	92.74%	97.53%	91.96%	97.91%	92.19%
255	97.49%	91.72%	97.36%	91.28%	97.89%	93.09%

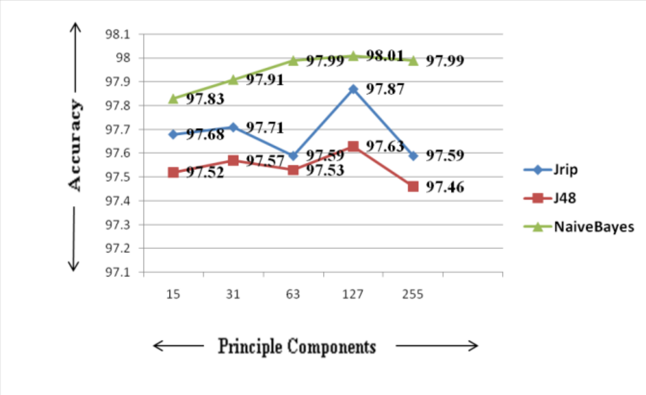

Fig.5 General Accuracy of the Jrip, J48 and Naïve Bayes applying PCA on the channel H as the input with using Post-SINR

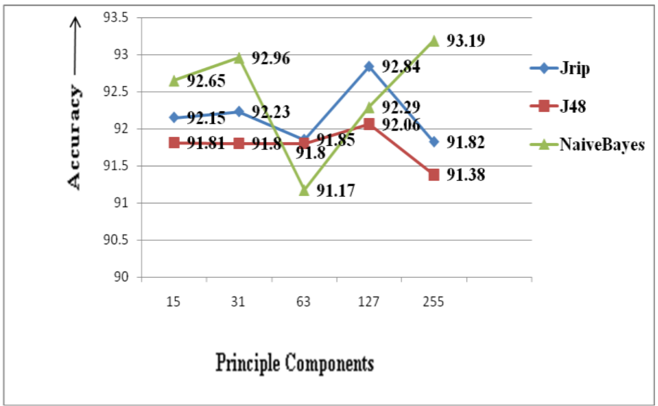

Fig.6 Decreasing Accuracy of the Jrip, J48 and Naïve Bayes applying PCA on the channel H as the input with using Post-SINR

After replacing the last principal component with the post-SINR, the below table shows good results with PCA. This test proves the hypothesis concerning the importance of the post-SINR. The Jrip, J48 and Naïve Bayes have respectively 92.74%, 91.96% and 92.19% descending accuracy in Table 4 is the best performance of 127 principal components and the post-SINR as the input features.

IV. CONCLUSION

In this research work, all three machine learning 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. Among the three algorithms, J48 performs the worst, which means it is not a suitable algorithm for this problem and the training time for the traditional J48 method is long. The advantage of Jrip is the short learning time with an acceptable accuracy. However, Jrip needs to use the post-SINR for prediction. Without using the post-SINR as the input, the performance of the J48 model is worse than the calibration method. The Naïve Bayes model has the best prediction accuracy and performs well without the post-SINR. However, the Naïve Bayes usually 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 Naïve Bayes model is the best algorithm for this problem and the suitable feature design is to directly use principal components.

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