Comparison of Automatic Modulation Classification Techniques

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Abstract —The advancement of digital communication and technology triggered new challenges related to the channel and radio spectrum utilization. From the other hand, real-time communications are keen of time where requests need to be processed in very short time. Automatic modulation is one of promising approaches that relies on pretrained classifiers in order to recognize the type of modulation techniques used by the transmitter. Considering that noise is dominating between the transmitter and receiver, the task of automatic modulation classification is become harder. Noise is destroying the obvious features of the signals and degrade the classification accuracy. The modulation identification technique is made to recognize the type of modulation using the deep learning technology. This paper is listing the common stat of the arts used in automatic modulation classification along with their performance measures. It was realized that deep learning classifier manifested in Conventional Neural Network (CNN) is outperformed in AMC scoring of 85.41 % of recognition accuracy.

Index Terms—Modulation, CNN, AMC, classification.

Nomenclature

Local Binary Pattern	LBP
Quadrature Amplitude Modulation	QAM
Extreme Learning Machine	ELM
Adaptive Modulation and Coding	AMC
Deep Neural Network	DNN
Centroids Of Constellation Points	COCP
High-Order Cumulants of Received Samples	HOCORS
Higher Order Moments	HOM
Instantaneous Characteristics	IC
Radial Basis Function	RBF
Multilayer Perceptron Neural Network	MLPNN
Multi-Class Support Vector Machine	MC-SYM
Maximum Likelihood Classifier	MLC
Amplitude/Phase Modulation	AM, PM
Minimum Distance Classifier	MDC
Closed Form Blind Source Separation	BSS
Quadrate Amplitude Shift Keying	QASK
Quadrate Frequency Shift Keying	QFSK
Quadrate Phase-Shift Keying	QPSK
Short-Time Fourier Transform	STFT
Fuzzy C-Means Clustering	FCMC
Long Short-Term Memory	LSTM
Space-Time-Block-Codes	STBC
Multiple-Input Multiple- Output	MIMO
Segmentary Neural Network	SNN
M-Ary Phase Shift Keying	MPSK
M-Ary Frequency Shift Keying	MFSK
Gaussian Minimum Shift Keying	GMSK
Offset-Qpsk	OQPSK
Two Threshold Sequential Algorithmic Scheme	TTSAS
Pattern Recognition	PR
Hamming Neural Network	HNN
Statistical Signal Characterization	SSC
Higher Order Spectra Features	HOSF
Learning Modulation Filter Networks	LMFNS
Unmanned Aerial Vehicle	UAV
Principal Component Analysis	PCA
Block-Based Discrete Wavelet Packet Transform	BDWPT
Random Forest Algorithm	RFA
Cognitive Radio Network	CRN
Modulation Recognition technique	MRT
Automatic Recognition of Modulation	ARM
Fifth Generation	5G

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I. INTRODUCTION

Digital communication is gained extra attention in several life sectors such as cellular networks, entertainment television, gaming, etc. The advancement of the said technology is witnessed after the introduction of high-speed data technology through 5G. The expansion of digital communications in various scales i.e., mobile networks and emerging of new digital technologies i.e., cognitive radio are behind the requirements of digital modulation identification. The same is termed as automatic recognition of signals which is keen on identification of the modulation techniques used to transmit the signal in order to perform the proper process for original data/signal recovery. Automatic signal recognition is an interested area in many applications including spectrum management, surveillance, noise elimination, signal processing, monitoring systems, etc.

Two possible ways are available for automatic modulation implementation includes analytical based recognition [1] and pattern recognition [2]. The first technique uses hypothesis based probabilistic roles in order to identify the signal; such is said to be difficult for implementation due to its computational high budget and complexity. From the other hand, pattern recognition is depended in many concerned studies as a reliable and cost-efficient alternative for signal identification. It uses computerized mining algorithm for classifying the signals into their original race. However, machine learning includes supervised and unsupervised learning are employed for signal classification in the second approach e.g., automatic recognition.

Pattern recognition may encounter a percentage of error while decision making, the amount of error is depending on learning quality in of the specific algorithm used for classification purpose. Generally, pattern recognition is easy for implementation and outperformed over the analytical recognition.

Implementation of pattern recognition can be performed in form of computerized algorithms (deep learning and machine learning). Thus, the structure of those systems can be prescribed in two subsystems namely features extraction and classification. The features extraction involves extraction of the concern attributes from the signal where those attributed are then used to represent the signal in the further process.

Features extraction from a communication signal involves finding the following information in the said modulated signal: zero-crossing, phase angle with signal amplitude, shape of constellation [3]-[5], signal Kurtosis, signal approximation using wavelet transform [6], signal representation in frequency domain [7]. From the other hand, the hereafter procedure involves signal classification using popular classification techniques alike random forest [8], k-nears neighbour [7], neural network [3], [9]-[12], etc.

However, automatic recognition of modulation can be scaled up to involve various sectors apart form communication as aforementioned, it can be used in electric traduces, measurement devices, power systems, medical applications, etc.

II. Related Studies

The need of extra spectrum bands in the radio communications motivated new innovations coming into light such as cognitive radio [2] and software defined radio [13]. The main tragedy of such technologies is to conduct efficient spectrum allocation and management. In order to do so, automatic signal classification/recognition was one of the worth doing approach due to cost consciousness and noticeable performance. The recent studies in this field are summarized in Table I. Mainly, automatic classification of communication signals was performed to recognize the modulation technique used to transmit the signal. Knowing that gives clarity on signal constriction which is needed to isolate/recover the original information from the modulated signal. Recognizing the modulation techniques through the mentioned procedure involves extracting the features corresponding to the modulation type. The said features are achievable through extraction the time domain, frequency domain and time-frequency domains related information form the test signals. Machine learning based classification can be used for recognizing of modulations such as Multi-Carrier Phase Shift Keying (MC-PSK), Frequency Shift Keying (MC-FSK) [7]. Modulated signal is generated at sender/transmitter side for transforming the raw data into compatible channel form. It can be essentially combating the noise and interferences taking place throughout signal voyage to the receiver. Thus, automatic signal classification may give proper attention to the noise and channel interference. Considering this drawback, features is treated with clustering algorithm called Neutrosophic C-means based Feature Weighting (NCMBFW) prior to the classification [7]. Classification is performed with Signal to Noise Ratio (SNR) of -5 dB using Extreme Learning Machine (ELM) which is said to have better performance than traditional machine learning classifiers in classification of Adaptive Modulation and Coding (AMC) [2]. SNR is tuned-up while classifying of Quadrature Amplitude Modulation (QAM) using deep learning unsupervised classifier i.e. Deep Neural Network (DNN); with SNR=0 best signal classification rate was achieved [3]. Number of features is said to be mattered for classification performance. Supervised classification is used at [13] and the classification rate of the signals is enhanced through using heuristic recognition for optimizing the results of classifier. Analytical automatic classification is proposed at [1], Maximum Likelihood Classifier (MLC) is used for the same. Computational complexity raised due to additional cost required for estimating of SNR prior to classification. Minimum Distance Classifier (MDC) is said to have good performance is predicting of SNR expect its reequipments for carrier phase offset correction. Short-Time Fourier Transform (STFT) is used to provide frequency representation of the signal to create another dimension along with time representation for fulfilment the 2D data input requirements at Convolutional Neural Network (CNN) [9]. Most dependable features of digital modulation can be extracted from constellation diagram. The geometrical features of constellation diagram are corresponded as a signature for digital modulation unless noise influences. Maximum Likelihood (ML) is used for classifying digital modulation through the constellation shape features. Thus, in order to retrieve the noise caused missing constellations, Fuzzy C-means Clustering (FCMC) was used [4]. For demodulation of baseband high-frequency digital modulated signal, Long Short-Term Memory (LSTM) is well performed in featureless automatic signal classification with SNR od 5 dB -25 dB [10]. Multiple-Input Multiple- Output (MIMO) modulated signal is another concern of automatic signal recognition which is being classified using DNN and RBF classifiers as explained in [11]. For high-speed communication, high frequency carriers are demanded which however outperformed using quadrate digital modulations which preserves four carriers for data transmission. Thus, double-fold transmission rate can be achieved compared to conventional modulations. At [12], quadrate ASK, FSK, PSK modulations are applied to achieve fast data transmission using various SNRs i.e. (5 dB-10 dB-15) while classifying the noisy modulated signal by Seminary Neural Network (SNN). Hamming neural network is used for implanting of Two Threshold Sequential Algorithmic Scheme (TTSAS) algorithm for recognizing QAM and PSK modulations at [5]. At low

SNR modulated signals are classified using Statistical Signal Characterization (SSC) techniques. SSC represents each modulated signal with four numerical values making it easier to train the ANN classifier at 3 dB SNR [14].

TABLE I: SAMPLE OF RECENT RESEARCH ACTIVITIES IN AUTOMATIC MODULATION CLASSIFICATION

Ref	Methods	Preprocessing	Modulations	Features	Metrics	Impressions
[1]	MLC	MDC, BCC	AM, PM	--	--	MDC is proposed for reduction of MLC computational cost. Then BCC is used for correction the carrier phase offset prior to the actual classification procedures.
[2]	ELM	--	AMC	LBP	Accuracy	Using of ELM instead of traditional ML
[3]	DNN	--	QAM	I-Q constellation points, COCP, HOCORS	Classification rate	Variation of SNR until 0 dB has achieved best per.
[4]	ML	FCMC	Candidate modulation	Constellation diagram geometry	--	FCMC is used to retrieve the noise caused missing constellations.
[5]	ANN	SSC	Any digital or analogue modulation.	Four numerical values resulted from SSC	Accuracy	Good classification at low SNR can be achieved with SSC.
[7]	RF, KNN, SVM, LDA, AdaBoostM1	Clustering by (NCMBFW)	MC-ASK, MC-FSK, MC-PSK	T, F, T&F domains	f-measure	Per. Is compared with/out NCMBFW and found better with NCMBFW.
[9]	CNN	STFT	ASK, FSK, PSK, QASK, QFSK, QPSK.	T & F	--	STFT used to provide freq. representation of signal which is used along with time representation to fulfil the 2D data input requirements at CNN.
[10]	LSTM	--	ASK, FSK, PSK	No features extraction	MAPE, MSE, R2, RMSE, NRMSE	SNR range (0-25 dB). Nosing of 5 dB to 25 dB is added to modulated signal and LSTM is outperformed as demodulator without needing for features extraction phase.
[11]	DNN, RBF	--	STBC- MIMO	--	CSI	--
[12]	SNN	While demodulating (classification) the quadrate modulated signal is being segmented into four groups and each group is being classified by one segment NN.	QASK, QFSK, QPSK	--	--	--
[13]	MLPNN, RBF, MC-SVM	PSO based classifier		HOM, HOCORS, IC	--	PSO used for optimizing the classifiers per.
[15]	ML	Chaotic sequences applied to secure the features of M-ary modulations.	MPSK,MFSK	Regular modulation features with chaotic sequence integration.	Recognition rate (acc.)	chaotic sequence integration degrade the classification performance hardly compared to none chaotic sequence.
[16]	TTSAS with PR	Fuzzy clustering	QAM, PSK	Constellation diagram geometry	Accuracy	TTSAS is implemented using HNN.

III. APPLICATIONS OF AMC

AMC has wide spread in plenty of technological applications. Many types of modulations including those used in underwater transmissions are leaked for security, however, chaotic sequences are used to code the features of the said modulated signals in order to block unauthorized receivers. AMC is applied for classifying the chaotic MPSK signal at high SNR, identification rate of the said signals are shown nearly to zero with AMC technique compared to 90% recognition rate when no chaotic sequences were applied [15]. AMC is used to estimate the SNR in None Data Aided (NDA) estimation of wireless networks through exploitation of three features namely bit-rate, modulation format and SNR related features in Asynchronous Delay-Tap Plots (ADTPs) which achieved as 99.12% accuracy [17]. Satellite transmissions involved using various modulations standards including linear modulations techniques such as MPSK for gaining higher robustness over hardware none-linearity. None linear modulations i.e. Gaussian Minimum Shift Keying (GMSK) can provide better spectrum efficiency. Furthermore, offset-QPSK (OQPSK)is decreasing the out band interferences. Such triggered a dispute over technology utilization by broadcasting companies. AMC (i.e. Bayesian classifiers) has drawn good performance in allowing of modulation diversity over satellite transmission by recognizing different race of signals [16]. Software-defined radios application has been utilized ANN classifier for recognizing M-APSK and DVB-S2X modulations using higher order spectra features (HOSF) at SNR=0 dB [18]. Learning filters is new technology adopted in signal processing which allows digital filter to learn from different experiences through the use of artificial intelligence for tackling the challenges of weak signals detection in unmanned aerial vehicle (UAV) communication [6], [19]. Principal component analysis (PCA) is used to classify digital mammograms information extracted by block-based discrete wavelet packet transform (BDWPT) [6]. The European 868 MHz has been utilized AMC for enhancing the short-range communication by using Random Forest Algorithm (RFA) based classification [8]. AMC is used while deployment of Cognitive Radio Network (CRN) in military applications. As the receiver know nothing about the modulation type of the incoming signals in CRN, conventional Higher-Order Statistics (HOS) features have been extracted from the signal to allow the classifier learning the behaviours of various signals for performing efficient spectrum sensing [20].

IV. Discussions and Conclusion

AMC is proven as efficient alternative for decomposing the signals. It has been employed at radio receivers acting as demodulator or at data mining systems for decision making. From the above survey, it was realized that AMC performs its tasks by merely depending on computerized software. That made the complex hardware to be dispensed in the relevant systems wherever this technology is adopted. The technology has faced different challenges due to the nature of radio signals and existence of noise. The corner stone of this technology are the artificial intelligence (machine learning and deep learning) tools. Thus, radio signal has been received by the respective receiver and passed into AMC subsystem where classification of the signal is taken place. Two types of AMC are recognized namely AI-AMC and Analytical AMC wherein the first is said to be outperformed over the other. Hereby, following points can be made in accordance with the approaches that were implementing this technology.

A. Pre-processing

As classification approaches are clean data oriented, the received signal (with is modulated by a carriers) are included with unwanted random in nature candidates (noise and interferences). Such candidates degrade the performance of classification. Thus, elimination of noise and interferences influences is vital for classification successes. That involves different filtering technologies as well as related to the qualification of the communication system itself such that using of particular transmission technologies such as orthogonal transmission may mitigate the noise impact.

B. Features

Mainly frequency and time based features are deployed by most of the concerned studies. Table I states most of the available information found in the respective studies. Hereby, the constellation diagram features are said as predominant at most of the studies and attributed by their robustness meaningful information that can clearly represents the modulation information.

C. Features Deficiency

Sometimes, the available features are not fitting the inputs constrains of classifier, more likely when one dimensional (1D) feature are existed whereas the classifier tolerance is 2D input. In such occurrences, BDWPT and FFT can be used for deriving of frequency representation of the signal which can be added into time representation for creating of two-dimensional data input.

D. Features-less Processing

Through using of deep learning classifiers such as LSTM, the phase of features extraction is eliminated and instead, raw data is being supplied into the classifier which preserved good recognition rate at different SNRs.

E. Supplementary Stages

Applying coding external sequences as alliances in the data segment for security purpose may degrade the classification performance as illustrated at [15].

F. Modulation Variation

Through the existence of multiple types of modulations, however, quadrate modulations such as (QASK, QFSK, QPSK) are outperformed in terms of fast transmission provision.

G. Performance Metrics

Accuracy of classification which is also termed as recognition rate is populated metric for measuring the performance of the classification process. However, other metrics were also realized such as MSE, MAE, RMSE, R2, f-measure and CSI. Nevertheless, various modulations techniques and various classification subsystems, the AMC preserves best accuracy at lower SNRs especially where SNR= 0 dB.

H. Optimization Algorithms

The optimization algorithms can be integrated with classifiers in order to enhance the classification accuracy, such that involves proposing of PSO for optimizing the learning coefficients in ANN.

Fig. 1 and Fig. 2 are demonstrating the popularities of both machine learning approaches as well as the modulation approaches in the selected samples of this paper.

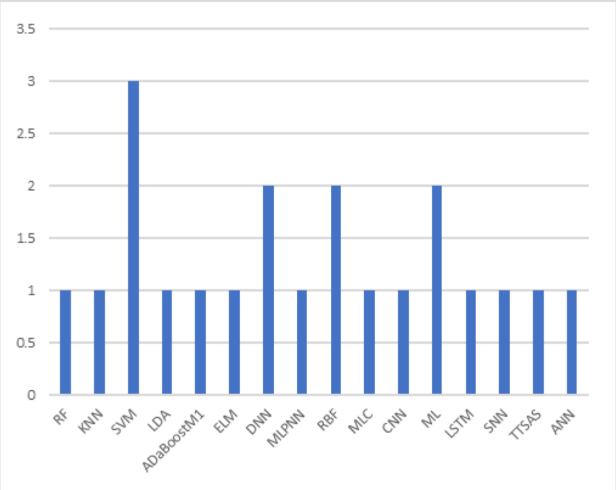

Fig. 1. Machine learning methods popularity

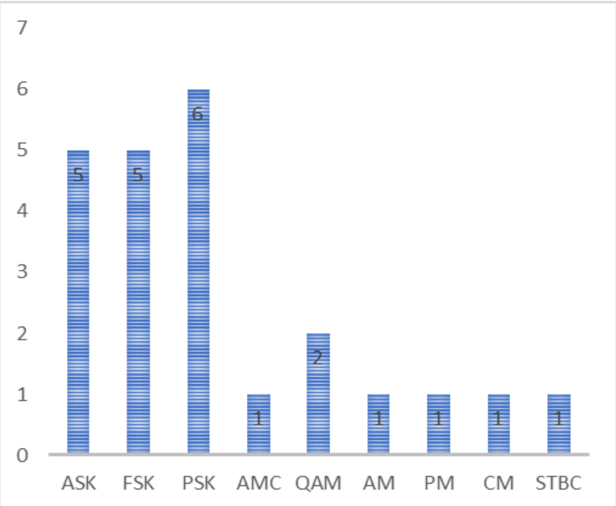

Fig. 2. Modulation technique popularity

V. Performance Study

Technologies used for modulation recognition including deep learning and machine learning as well as the pre-processing as mentioned at Table I are varying in terms of recognition accuracy, Table II is demonstrating the accuracy of AMC systems. (See Fig. 3, Fig. 4, and Table III).

TABLE II: ACCURACY SCORES OF AUTOMATIC MODULATION RECOGNITION TECHNOLOGIES AS PER LITERATURE ILLUSTRATED IN TABLE I.

Ref.	Methods	Recognition Accuracy
[1]	MLC	66.22
[2]	ELM	77.2
[3]	DNN	84.32
[4]	ML	64.16
[5]	TTSAS with PR	77.77
[7]	RF, KNN, SVM, LDA, AdaBoostM1	42.21, 67.40, 55.92, 75.32, 51.43
[9]	CNN	85.41
[10]	LSTM	79.99
[11]	DNN, RBF	81.9, 67.3
[12]	SNN	84.32
[13]	MLPNN, RBF, MC-SVM	76.15, 62.41,68.22
[14]	ANN	78.29
[15]	ML	75.11

TABLE III: MAE SCORES OF AUTOMATIC MODULATION RECOGNITION TECHNOLOGIES AS PER LITERATURE ILLUSTRATED IN TABLE I.

Ref.	Methods	MAE
[1]	MLC	0.178
[2]	ELM	0.121
[3]	DNN	0.091
[4]	ML	0.622
[5]	TTSAS with PR	0.122
[7]	RF, KNN, SVM, LDA, AdaBoostM1	0.225, 0.143, 0.199, 0.113, 0.152
[9]	CNN	0.0892
[10]	LSTM	0.0811
[11]	DNN, RBF	0.0721, 0.231
[12]	SNN	0.0512
[13]	MLPNN, RBF, MC-SVM	0.021, 0.149, 0.233
[14]	ANN	0.1
[15]	ML	0.182

From the other hand, MSE can be demonstrated in Table IV and depicted in Fig. 5.

TABLE IV: MSE SCORES OF AUTOMATIC MODULATION RECOGNITION TECHNOLOGIES AS PER LITERATURE ILLUSTRATED IN TABLE 1.

Ref.	Methods	MSE
[1]	MLC	2.178
[2]	ELM	2.121
[3]	DNN	2.091
[4]	ML	2.622
[5]	TTSAS with PR	2.122
[7]	RF	2.225
[7]	KNN	2.143
[7]	SVM	2.199
[7]	LDA	2.113
[7]	AdaBoostM1	2.152
[9]	CNN	2.0892
[10]	LSTM	2.0811
[11]	DNN	2.0721
[11]	RBF	2.231
[12]	SNN	2.0512
[13]	MLPNN,	2.021
[13]	MC-SVM	2.149
[13]	RBF	2.233
[14]	ANN	2.1
[15]	ML	2.182

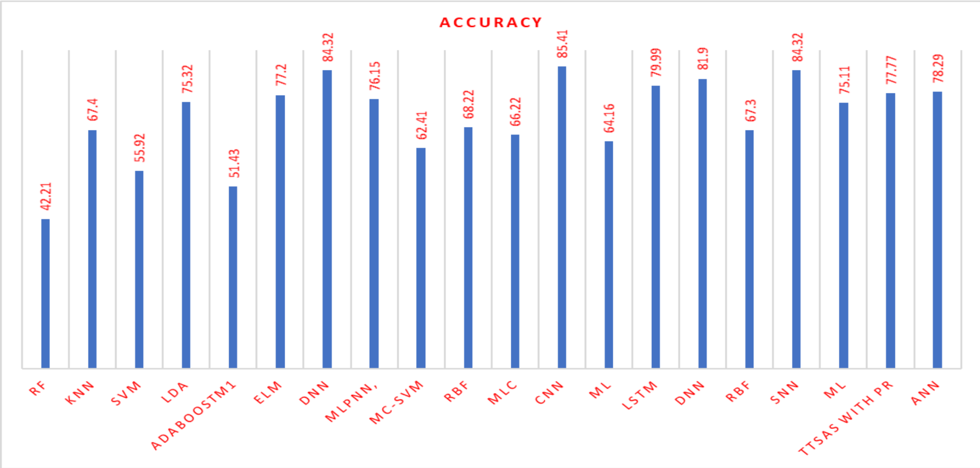

Fig. 3. Accuracy scores for the AMC technology as illustrated in Table II.

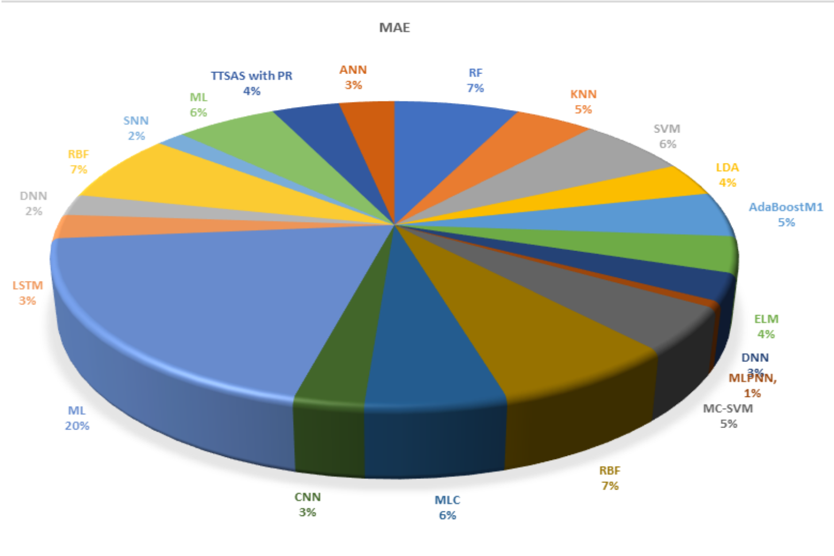

Fig. 4. MAE scores for the AMC technology as illustrated in Table III.

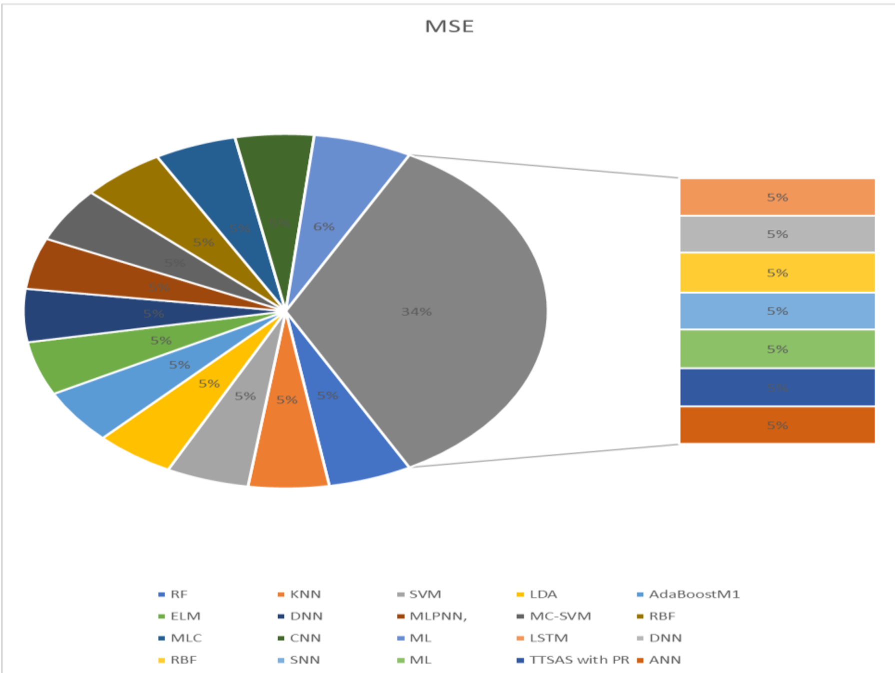

Fig. 5. MSE scores for the AMC technology as illustrated in Table IV.

Conflict of Interest

The authors no conflict of interest.

Author Contributions

Salah Ayad Jassim has prepared and analyzed the data, reviewed the research, and proofread the english language; Ibrahim Khider has modified the paper organization and outline. All authors had approved the final version.

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