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Research Article

Keywords: Hierarchical Modulation Classification, Feature Extraction, Machine Learning Algorithms, Support Vector Machine, Analog Modulations, Digital Modulations

Posted Date: August 8th, 2022

DOI: https://doi.org/10.21203/rs.3.rs-1780652/v1

Hierarchical Classification of Analog and Digital Modulation Schemes using Higher-Order Statistics and Support Vector Machines

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Abstract

Automatic Modulation Classification (AMC) algorithms play an important role in various military and civilian applications. There have been numerous AMC algorithms reported in the literature, most of which focus on synthetic signals with a limited number of modulation types having distinctive constellations. The efficient classification of high-order modulation schemes under real propagation effects using models with low complexity is still a challenge. In this paper, employing quadratic SVM, a feature-based (FB) hierarchical classification method is proposed to accurately classify especially higher-order modulation schemes and its performance is investigated using over the air (OTA) collected data. Statistical features, higher-order moments, and higher-order cumulants are employed as features. Then, the performances of some well-known classifiers are evaluated, and the classifier presenting the best performance is employed in the proposed hierarchical classification model. An OTA dataset containing 17 analog and digital modulation schemes is used to evaluate the performance of the proposed classification model.

With the proposed hierarchical classification algorithm, a significant improvement has been achieved, especially in higher-order modulation schemes. The overall accuracy with the proposed hierarchical structure is 96% after 5 dB signal-to-noise ratio (SNR) value, approximately a 10% increase is achieved compared to the traditional classification algorithm.

Keywords: Hierarchical Modulation Classification, Feature Extraction, Machine Learning Algorithms, Support Vector Machine, Analog Modulations, Digital Modulations.

1 Introduction

Automatic Modulation Classification (AMC) is a major task in a wide range of military and civilian communication applications [1]. AMC algorithms can be divided into two main groups likelihood-based (LB) [2] and feature-based (FB) [3] approaches in the literature. LB approaches are based on maximum likelihood ratio testing. By making predictions on the probability density function (pdf) of the received signal, the classification is achieved through thresholding [4]. LB approaches give the optimal solution, however, they are mostly not preferable due to the sensitivity to model mismatches and non-ideal situations, i.e., frequency offsets, phase and timing errors, and noise along with high computational complexity [5]. A few LB approaches have been proposed [6–9], including Average Likelihood Ratio Test (ALRT), Generalized Likelihood Ratio Test (GLRT), Hybrid Likelihood (HLRT), and Quasi-Hybrid Likelihood Ratio Test (QHLRT). On the other hand, FB approaches simply focus on the extraction of features from the signals to be classified are easier to implement, and have lower computational complexity [10, 11]. The selection of features that are unique in discriminating the modulation schemes play a critical role in classification performance since the type of the features might also affect the type of the classification methods to be used along with expected channel perturbations or effects [12]. A variety of time and frequency domain based features have been reported in the literature including higher-order statistics (HOS), Wavelet, and Fourier transform of the signals [13–26].

There have been many reports regarding the performance of classifiers in AMC applications employing FB approach for some basic modulation schemes (analog or digital-binary-modulation schemes) [27]. The classifiers based on traditional machine learning (ML) algorithms are available in the literature mainly as k-nearest neighbors (KNN), decision trees, and support vector machines (SVM). The performance and complexity of each classifier type under various practical conditions are studied well in the literature. KNN algorithm assigns the unknown data to the class with the most similar data of the training set. This classifier may not give acceptable performance for high dimensions. It also requires relatively high memory which results in low processing speed. There are many types of KNN with varying flexibilities i.e., fine, medium, and coarse KNN. The decision tree is a frequently preferred structure in data mining applications due to lower processing speed and memory requirement. On the other hand, it has been reported to be poor when the number of features is less, or the number of classes is high. There are several types of decision tree algorithms as well with different flexibilities i.e., fine, medium, and coarse trees. SVM is highly preferred for classification as it presents high performance along with low computational complexity [28]. Therefore, the use of SVM has increased incredibly as compared with the other classifiers [29]. SVM employs support vectors to find a hyperplane that distinguishes the data points belonging to different classes. At first glance, SVM or a similar classifier along with a unique set of features would then seem to be a promising ML configuration for AMC implementation for some basic modulation schemes. However, the performance of such ML algorithms for higher-order modulation schemes has not been thoroughly studied [30]. Additionally, there is a limited number of works regarding ensemble methods with voting approaches for modulation classification in the literature. Ensemble classifier uses multiple classifiers unitedly to increase the accuracy. Bagged and Boosted methods are two commonly used ensemble methods. Their prediction speed generally remains low due to the multiple learner structure. The memory requirement may vary according to the method. Model flexibility of this type of classifier is generally reported as high [31]. High accuracy has not been reported at, especially, low SNR values although the number of modulations to be classified is limited [32–34]. Besides, misclassification of similar types of modulation schemes is still a problem. Recently, deep learning (DL) based methods have been proved to outperform in feature extraction and classification. However, preprocessing of the received signal is still a challenge and DL generally requires long training data size as well as high computational cost or complexity [12]. When there is a relatively small amount of records of the signals to be classified, DL based classification might be challenging work [35, 36]. Therefore, classical ML-based AMC implementations can still be considered as an effective option. In ML implementations, hierarchical classification has been proposed to classify diverse signal types, i.e., radar signals and underwater communication signals. In [37], hypothesis testing is utilized hierarchically and FB modulation classification is employed for modulation orders up to 16. Classification for frequency modulation schemes is reported in [38] by adopting cascade systems, and [39] by using a Naive Bayes classifier. In [40], a hierarchical deep neural network is proposed for the classification of low-level modulation schemes. Finally, there have been a few more hierarchical methods that have been reported in the literature, such as FB using cumulants and thresholds for decision making or polynomial classification [41–44]. In most of the reported works, a limited number of hierarchical methods are applied only to some specific low-order modulation schemes. Additionally, almost all of the published works report performance analysis under simulated Additive White Gaussian Noise (AWGN) channel conditions which do not represent real propagation channel perturbations [45]. Besides, the performances of classification of higher-order modulation schemes are mostly unsatisfactory at low signal-to-noise ratio (SNR) values [46, 47]. A few hierarchical classifiers have been reported [48, 49] however they seem to be impractical as they utilize many stages and classifiers which makes them highly complex. Considering the trade-off of the low complexity and high success, these types of structures generally remain insufficient despite their high accuracy. Finally, it is still a challenge to present an efficient FB method with a relatively short processing time, as well as classify diverse modulation schemes with similar constellations including higher-order modulated signals having real propagation effects with high accuracy.

In this study, employing quadratic SVM, a FB hierarchical classification structure is proposed for AMC of 17 different modulation schemes consisting of i) analog modulation schemes (Single Sideband, Double Sideband, and Frequency Modulation) ii) digital modulation schemes (On-Off Keying, M-ary Amplitude Shift Keying with M=4,8, M-ary Phase Shift Keying with M=2,4,32, M-ary Amplitude Phase Shift Keying with M=16,32,64,128, M-ary Quadrature Amplitude Modulation with M=16,64, Offset Quadrature Phase Shift Keying and Gaussian Minimum Shift Keying). In our previous work, we presented a performance comparison of several different FB traditional classifiers by employing 14 modulation schemes. Using quadratic SVM as a classifier, 98% overall accuracy was achieved at a 10 dB SNR value [50]. However, in the case of employing a dataset containing higher-order modulation schemes with similar constellations, traditional modulation classification algorithms remain insufficient to classify these types with high accuracy. Here, we propose a method combining hierarchical structure with ensemble classification approach to accurately classify higher-order modulation schemes with similar constellations.

- A hierarchical modulation classification is presented with relatively higher accuracy but relatively lower complexity (lower elapsed time).
- The performance comparison of the proposed method with 18 different well-known classifiers including traditional SVMs is reported for realistic channel effects.
- A series of analog and digital modulation schemes containing similar constellations and higher orders are accurately classified by using the proposed hierarchical classification model.
- A high-level overview of the methods used in the literature, classified modulation types, accuracy rates and studied SNR levels is presented.

The rest of the paper is organized as follows: In Section II, the signal preprocessing and higher-order statistical features along with the proposed classification algorithm are detailed. Section III presents the performance of the proposed classification method along with the comparison of some well-known classifiers. Section IV draws conclusions and future works.

2 Proposed Method

Feature extraction and classification are two main stages in FB-AMC. First of all, features must be selected in accordance with the modulation types. The extraction process includes the usage of signal processing algorithms and estimations of signal properties such as amplitude, phase, and frequency. The classification operation should then be performed with a classifier suitable for features, channel conditions, modulation, and signal types. The proper functioning of the classifier largely depends on the selection of appropriate features.

2.1 Signal Dataset and Preprocessing

Radio signals acquired under different channel conditions, their SNR values, and modulation schemes affect the classification performance greatly. In this work, modulated OTA signals available in [51] containing modulation types listed in the previous section are used. The signals are provided in in-phase/quadrature (I/Q) form with 1024 samples for each recording. There are 4096 signal recordings at each SNR value (from 0dB to 30 dB with 2dB steps) for each modulation type.

The analytical expression for any sequence of complex I/Q signal components at a specific time sample $n(n = 1, 2, , N)$ is given as

$$s(n) = I(n) + jQ(n) \tag{1}$$

Next, the instantaneous amplitude $a(n)$, instantaneous phase $\phi(n)$, and instantaneous frequency $f(n)$ of the signal given in (1) can be respectively written as

$$a(n) = \sqrt{I^2(n) + Q^2(n)} \tag{2}$$

$$\phi(n) = tan^{-1}[\frac{Q(n)}{I(n)}] \tag{3}$$

$$f(n) = \frac{1}{2\pi} \frac{(\phi(n) - \phi(n-1))}{\Delta n} \tag{4}$$

Instantaneous signal characteristics are centered by removing mean values (μ) in order to avoid systematic bias. Moreover, linear component of the instantaneous frequency is also removed for incorrect estimation of frequency at the down-conversion stage [52]. The centered amplitude $a_c(n)$, phase $\phi_{cnl}(n)$ and frequency $f_c(n)$ can be derived as follows

$$a_c(n) = a(n) - \mu_a \tag{5}$$

$$f_c(n) = f(n) - \mu_f \tag{6}$$

$$\phi_{nl}(n) = \phi(n) - 2\pi\mu_f(n)\Delta_t \tag{7}$$

$$\phi_{cnl}(n) = \phi_{nl}(n) - \mu_{\phi_{nl}} \tag{8}$$

where $n(n = 1, 2, , N)$ is the sample number of the signal, and Δ_t is the duration between time samples [53].

2.2 Feature Extraction

Based on the literature discussed in the previous section, a total of 41 features consisting of HOS and extracted from the instantaneous characteristics $a_c(n)$, $\phi_{cnl}(n)$, and $f_c(n)$ are employed. The use of statistical features instead of instantaneous characteristics directly provides lower computational complexity, smaller feature space, and better performance at low SNR values. Each feature is computed from 1024 samples of the signal. For any instantaneous signal characteristic $x(k)$, that is, $a_c(n)$,$f_c(n)$ and $\phi_{cnl}(n)$, the following well-known features mean (μ_x), variance (σ_x^2), skewness (γ_x) and kurtosis (κ_x) can be defined as

$$\mu_x = \frac{1}{N_x}\sum_{k=1}^{N_x} x(k) \tag{9}$$

$$\sigma_x^2 = \frac{1}{N_x}\sum_{k=1}^{N_x}[x(k) - \overline{x}]^2 \tag{10}$$

$$\gamma_x = \frac{1}{\sigma_x^3 N_x}\sum_{k=1}^{N_x}[x(k) - \overline{x}]^3 \tag{11}$$

$$\kappa_x = \frac{1}{\sigma_x^4 N_x}\sum_{k=1}^{N_x}[x(k) - \overline{x}]^4 \tag{12}$$

where $\overline{x}$ is the mean value of $x(k)$ [44].

Additionally, higher order moments (HOM) and higher order cumulants (HOC) can also be computed for each of the signal characteristics as they are known to be resistant to noise. In general, HOMs ca be defined, as in [15], as follows

$$M_{pq} = \frac{1}{N}\sum_{n=1}^{N} s[n]^{p-q}.s[n]^{*q} \tag{13}$$

where p is the order of the moment, s^* is the complex conjugate of s, and q is the power of the conjugate signal s^*. Next, higher order cumulants (HOC) can easily be computed from HOMs. To set an example, computation of C_{60} can be indicated as follows [11]

$$C_{60} = M_{60} - 15M_{20}M_{40} + 30{M_{20}}^3 \tag{14}$$

where C denotes the cumulants with order as subscript. HOCs are not only known to be immune to rotation and excursion over the constellation diagram but also eliminate the effects of Gaussian noise. The feature set includes all moments and cumulants up to 8^{th} order. It should be noted that all cumulants need to be normalized for deviation problems at the classification stage. This can be achieved by increasing the power of cumulants (C_{pq}) to $2/p$. For example, the normalized cumulant for C_{82} can be obtained as

$$\hat{C}_{82} = C_{82}^{\frac{2}{8}} = C_{82}^{\frac{1}{4}} \tag{15}$$

The magnitude of the HOMs and HOCs can be used by ignoring the phase as it may cause shifting in the constellation while magnitude only processing reduces the computational cost [54].

In this work, three main feature sets are utilized; the set based on instantaneous signal characteristics is sufficient for discriminating analog modulation schemes while that of HOMs is effective at low SNR values. Finally, the last set containing HOCs is used for discriminating higher-order modulation schemes. Overall, a feature space consisting of all these feature sets is created for the accurate classification of a variety of modulation schemes at a wide range of SNR levels.

2.3 Classification

After the feature extraction process, SVM is employed for classification. SVM offers ease of use by removing computational complexity and providing high accuracy. It uses a hyperplane to separate classes. The objective is to find the hyperplane which passes from the maximum distance between the data points from two different classes that are closest to each other [34, 50]. These particular data points are known as support vectors. When the data points cannot be separated linearly, the non-linear classification of SVM can be used with the kernel trick. Employing the polynomial kernel of the SVM, the nonlinear classification can be performed; thus, linear, quadratic, and cubic derivations of the classifier can be obtained [44, 55]. The common problem in many classification algorithms is that one algorithm is not adequate to separate different modulation types with high accuracy in some cases such as in low SNR or different modulation types with similar constellations. The type and the order of the modulation classes, as well as the feature set, affect significantly the performance of the classifier. While the classifiers may be successful in separating some classes in the dataset, they may fail for some others. The flexibility of the classifier could be increased to increase the accuracy though this may cause overfitting. Moreover, prediction speed and memory requirement as well as difficulty in interpretability should also be studied. In this work, the performances of several well-known classifiers are compared and quadratic SVM is employed for the proposed hierarchical classification structure as it outperforms.

The proposed hierarchical classification structure is based on the constellation structures and confusion between different modulation schemes in the dataset. In the first stage, all of the modulation schemes in the dataset are trained and tested with the traditional quadratic SVM classifier. Then, the confusion matrices generated from the test set are examined at different SNR values. The modulation types with a high accuracy rate are classified at the first stage. The remaining modulation schemes that are mostly confused with each other are chosen as an input to the second stage classifiers. In the second stage, two parallel classifiers are trained with different modulation schemes. The decision on which classifier is trained with which modulation types is made according to the confusion and constellation similarities. Based on the confusion matrices of the test set at the first stage classification, the modulation types that are confused with each other are determined. In the second stage, the modulation types that are mostly confused with each other, such as 64-APSK and 128-APSK, are trained with different classifiers. For achieving a high accuracy rate, the groups of modulation schemes with similar constellations -but not highly confused- are selected and trained with the same classifier. By this means, the misclassification is greatly reduced. The structure of the proposed hierarchical SVM can be summarized as follows;

- Signals containing 17 different modulation schemes are trained and tested with the traditional quadratic SVM classifier (C1) and the confusion matrices are obtained.
- Confusion matrices at different SNR values from 0 dB to 30 dB are examined and the modulation types that classify with high accuracy are determined. These schemes are classified at the first stage.
- The remaining modulation schemes that are highly confused are given to the second stage for classification.
- Second stage contains two parallel quadratic SVMs (C2 and C3) as sub-classifiers trained with different groups of modulations. These modulation groups are determined based on the following criteria;

  -Highly confused modulation types are trained in different classifiers (such as 16-QAM and 64-QAM).

  -Each modulation scheme is utilized separately and the schemes that do not greatly confuse with each other are trained in the same classifier (16-QAM and 64-APSK).

  -Care was taken that a modulation type selected to train in C2 would confuse with at least two other modulation types trained in C3 when given to C3 during the testing process. Thus, this modulation type will confuse with other modulation types and its accuracy will decrease in C3, and at the same time, it will be correctly classified in C2 with a high rate. The same process is applied to C3 simultaneously. By this means, the misclassification at the parallel classifiers is avoided.
- In the testing process of the second stage, test signals will be given to the two parallel classifiers. Test signals will be classified correctly with a high accuracy rate in the classifier trained with the test signals modulation type. In the other classifier, the test signals will be confused with different modulation types and the classification accuracy will be reduced. Based on the ensemble classification approach, the testing accuracies of an individual modulation type in the second stage classifiers C2 and C3 are considered

as their weighted votes. The higher rated (voted) modulation type will be considered correctly classified.
- At the end, the classifier with the correct modulation scheme will be outperformed due to the structure of the proposed hierarchical scheme.

3 Results and Discussion

As discussed previously, 17 analog and digital modulation schemes are classified with traditional and hierarchical methods.

3.1 Traditional Classification Models

Firstly, 18 different classifiers including decision trees, SVMs, and KNNs are trained and tested in the MATLAB/Classification Learner toolbox in order to evaluate and compare their performance at 0 dB, 10 dB, and 20 dB. Table 1 presents the performances of the classifiers. By this means, the benchmarking of widely used classifiers in the AMC classification stage is provided. When the performances presented in Table 1 are examined, polynomial derivatives of SVM outperform all others. For different SNR levels, these classifiers show similar performance which seems to be more consistent. In Table 1, the classifiers showing similar performance are grouped and approximate accuracy (within 3% deviation) is reported for each SNR level.

Table 1 Performance comparison of some well-known classifiers at three different SNR levels

	Performances (%)		
Classifiers	0 dB	10 dB	20 dB
Fine/Medium Tree	46	78	79
Coarse Tree	27	29	29
Linear/Quadratic/Cubic SVM	50	86	86
Fine Gaussian SVM	35	72	72
Medium/Coarse Gaussian SVM	50	83	84
Fine/Medium/Coarse/Cosine/Weighted KNN	43	76	79
Boosted/Bagged Trees	48	80	81
Subspace Discriminant/RUSBoosted Trees	46	75	79

While classifying noisy signals, algorithms that have high flexibility could model the small changes due to the noise in the signal structure, causing an overfitting problem. Among the classifiers shown in Table 1, it has been observed that Fine Gaussian SVM, Fine KNN, Weighted KNN, Bagged Trees, and Cubic SVM - since it is known that Cubic SVM is more flexible than Linear and Quadratic SVM - classifiers face overfitting problems. To prevent this issue from occurring, 5-fold cross-validation is used for all of the experiments.

When we compare the classification performances given in Table 1 with the results in [34] and our previous work [50], it can be clearly seen that traditional classification methods fail to satisfy achieving high accuracy in the case of classifying higher-order similar constellation modulation schemes.

Figure 1 presents the average classification accuracy of Linear, Quadratic, and Cubic SVMs, where 80% of the dataset is used in training while the remaining is used in testing, for all modulation types (averaging of accuracy over all modulation types at 2 dB SNR increments). It is evident that there is no significant difference between the SVM derivations. However, quadratic SVM seems to perform slightly better after 10 dB SNR.

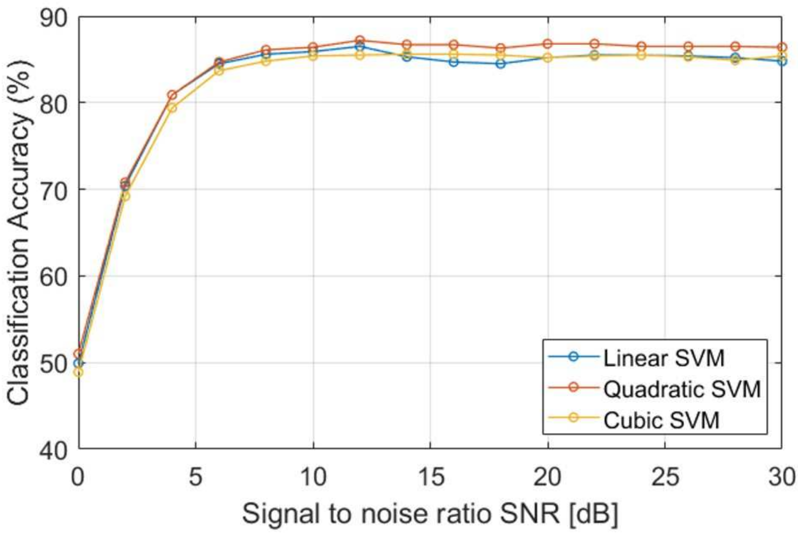


Fig. 1 Classification performances for linear, quadratic and cubic SVMs

Next, the confusion matrices are examined for detailed view of the classification as per modulation scheme. Shown in Figure 2 and Figure 3 are confusion matrices for all 17 modulation schemes at 0 dB and 10 dB SNR only as there is no significant change in the performance after 10 dB.

The accuracy of higher-order amplitude-phase modulation schemes is found very low at 0 dB SNR. Classification accuracy is increased to 86% from 51% for the same set of modulation schemes when SNR was increased to 10 dB. However, it is still observed as pretty much low for some higher modulation schemes (64-APSK and 128-APSK as well as 16-QAM and 64-QAM). When the performances at different SNR values are examined, it can be seen that the classifier is not affected by noise variations while classifying OOK and AM-SSB-SC because of their constellation structures. In contrast, especially QPSK, 32-PSK, 16-APSK, 32-APSK, 16-QAM, 64-QAM, and OQPSK modulations are more sensitive to SNR variations. It can be concluded that M-APSK (M>16) and higher-order QAM modulation schemes are likely to be misclassified even if the SNR is increased. These could be, to some extent, attributed to the complex constellation diagram of the higher-order modulation schemes.

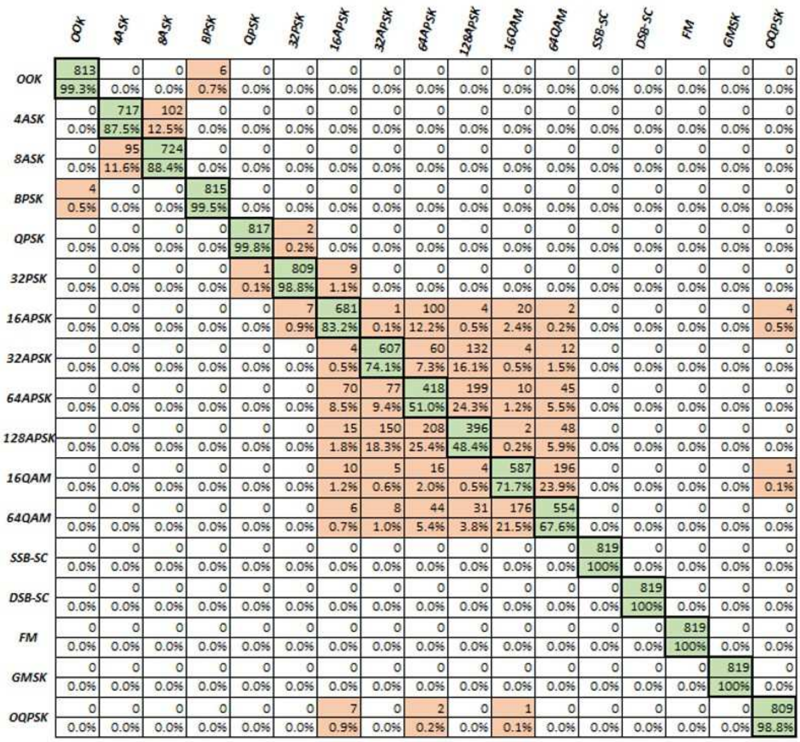
	OOK	4ASK	8ASK	BPSK	QPSK	32PSK	16APSK	32APSK	64APSK	128APSK	16QAM	64QAM	SSB-SC	DSB-SC	FM	GMSK	OQPSK
OOK	777	35	0	7	0	0	0	0	0	0	0	0	0	0	0	0	0
	94.9%	4.3%	0.0%	0.9%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
4ASK	23	590	205	0	0	0	0	0	0	0	0	0	1	0	0	0	0
	2.8%	72.0%	25.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.0%	0.0%	0.0%	0.0%
8ASK	0	187	630	0	0	0	0	0	0	0	0	0	1	0	0	0	1
	0.0%	22.8%	76.9%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.0%	0.0%	0.0%	0.1%
BPSK	1	0	0	727	0	0	0	0	0	0	0	0	0	91	0	0	0
	0.1%	0.0%	0.0%	88.8%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	11.1%	0.0%	0.0%	0.0%
QPSK	0	0	0	0	460	68	32	2	10	5	64	21	0	0	19	69	69
	0.0%	0.0%	0.0%	0.0%	56.2%	8.3%	3.9%	0.2%	1.2%	0.6%	7.8%	2.6%	0.0%	0.0%	2.3%	8.4%	8.4%
32PSK	0	0	0	0	61	273	116	13	44	15	33	15	0	0	47	143	59
	0.0%	0.0%	0.0%	0.0%	7.4%	33.3%	14.2%	1.6%	5.4%	1.8%	4.0%	1.8%	0.0%	0.0%	5.7%	17.5%	7.2%
16APSK	0	0	0	0	36	146	153	63	91	81	53	38	0	0	11	38	109
	0.0%	0.0%	0.0%	0.0%	4.4%	17.8%	18.7%	7.7%	11.1%	9.9%	6.5%	4.6%	0.0%	0.0%	1.3%	4.6%	13.3%
32APSK	0	0	0	0	13	26	61	276	123	112	62	82	0	0	1	3	60
	0.0%	0.0%	0.0%	0.0%	1.6%	3.2%	7.4%	33.7%	15.0%	13.7%	7.6%	10.0%	0.0%	0.0%	0.1%	0.4%	7.3%
64APSK	0	0	0	0	15	53	125	158	147	88	62	70	0	0	5	5	91
	0.0%	0.0%	0.0%	0.0%	1.8%	6.5%	15.3%	19.3%	17.9%	10.7%	7.6%	8.5%	0.0%	0.0%	0.6%	0.6%	11.1%
128APSK	0	0	0	0	18	41	88	193	141	128	62	73	1	0	3	4	67
	0.0%	0.0%	0.0%	0.0%	2.2%	5.0%	10.7%	23.6%	17.2%	15.6%	7.6%	8.9%	0.1%	0.0%	0.4%	0.5%	8.2%
16QAM	0	0	0	0	82	66	76	87	70	72	133	145	0	0	6	9	73
	0.0%	0.0%	0.0%	0.0%	10.0%	8.1%	9.3%	10.6%	8.5%	8.8%	16.2%	17.7%	0.0%	0.0%	0.7%	1.1%	8.9%
64QAM	0	0	0	0	43	45	73	123	95	59	133	158	0	0	3	7	80
	0.0%	0.0%	0.0%	0.0%	5.3%	5.5%	8.9%	15.0%	11.6%	7.2%	16.2%	19.3%	0.0%	0.0%	0.4%	0.9%	9.8%
SSB-SC	0	0	0	0	5	0	0	0	0	0	0	0	814	0	0	0	0
	0.0%	0.0%	0.0%	0.0%	0.6%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	99%	0.0%	0.0%	0.0%	0.0%
DSB-SC	0	0	0	269	0	0	0	0	0	0	0	0	0	550	0	0	0
	0.0%	0.0%	0.0%	32.8%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	67%	0.0%	0.0%	0.0%
FM	0	0	0	0	13	29	7	0	3	0	1	1	0	0	657	106	2
	0.0%	0.0%	0.0%	0.0%	1.6%	3.5%	0.9%	0.0%	0.4%	0.0%	0.1%	0.1%	0.0%	0.0%	80%	12.9%	0.2%
GMSK	0	0	0	0	58	137	19	0	4	2	4	0	0	0	107	476	12
	0.0%	0.0%	0.0%	0.0%	7.1%	16.7%	2.3%	0.0%	0.5%	0.2%	0.5%	0.0%	0.0%	0.0%	13.1%	58%	1.5%
OQPSK	0	0	0	0	85	132	105	41	77	46	79	61	0	0	7	32	154
	0.0%	0.0%	0.0%	0.0%	10.4%	16.1%	12.8%	5.0%	9.4%	5.6%	9.6%	7.4%	0.0%	0.0%	0.9%	3.9%	18.8%

Fig. 2 Confusion Matrix for Quadratic SVM (SNR=0dB)

For higher-order M-APSK schemes, misclassification is observed as higher than M-QAM. This is because M-APSK schemes have additional dimension (phase) compared with M-QAM schemes. Then, the next section presents a hierarchical classification technique in order to discriminate these higher-order modulation schemes. It should be noted that the classification accuracy of OOK, 8ASK, M-PSK (M=2,4,32), 32APSK, GMSK, OQPSK, SSB, DSB, and FM seems to be classified with a relatively higher rate than the others.

3.2 Hierarchical Classification Model

The proposed hierarchical classification algorithm constructed as two-stage classifications basically makes use of the performance of the SVM classifiers in the previous section. To this end, the traditional classifier (C1) is firstly trained with 17 modulation classes. Based on the results in the previous section, 11 modulation classes including OOK, 8ASK, BPSK, QPSK, 32-PSK, 32-APSK, SSB, DSB, FM, GMSK and OQPSK are classified accurately at the first stage. Here, if the classifier classifies the unknown signal as one of these 11 modulation types, it is declared to be correct. Otherwise, none of the classes is declared, and then the next two parallel classifiers (denoted by C2 and C3) are initiated with the same input samples. The two classifiers are trained in parallel for



	OOK	4ASK	8ASK	BPSK	QPSK	32PSK	16APSK	32APSK	64APSK	128APSK	16QAM	64QAM	SSB-SC	DSB-SC	FM	GMSK	OQPSK
OOK	813 99.3%	0 0.0%	0 0.0%	6 0.7%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%
4ASK	0 0.0%	717 87.5%	102 12.5%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%
8ASK	0 0.0%	95 11.6%	724 88.4%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%
BPSK	4 0.5%	0 0.0%	0 0.0%	815 99.5%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%
QPSK	0 0.0%	0 0.0%	0 0.0%	0 0.0%	817 99.8%	2 0.2%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%
32PSK	0 0.0%	0 0.0%	0 0.0%	0 0.0%	1 0.1%	809 98.8%	9 1.1%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%
16APSK	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	7 0.9%	681 83.2%	1 0.1%	100 12.2%	4 0.5%	20 2.4%	2 0.2%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	4 0.5%
32APSK	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	4 0.5%	607 74.1%	60 7.3%	132 16.1%	4 0.5%	12 1.5%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%
64APSK	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	70 8.5%	77 9.4%	418 51.0%	199 24.3%	10 1.2%	45 5.5%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%
128APSK	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	15 1.8%	150 18.3%	208 25.4%	396 48.4%	2 0.2%	48 5.9%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%
16QAM	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	10 1.2%	5 0.6%	16 2.0%	4 0.5%	587 71.7%	196 23.9%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	1 0.1%
64QAM	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	6 0.7%	8 1.0%	44 5.4%	31 3.8%	176 21.5%	554 67.6%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%
SSB-SC	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	819 100%	0 0.0%	0 0.0%	0 0.0%	0 0.0%
DSB-SC	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	819 100%	0 0.0%	0 0.0%	0 0.0%
FM	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	819 100%	0 0.0%	0 0.0%
GMSK	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	819 100%	0 0.0%
OQPSK	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	7 0.9%	0 0.0%	2 0.2%	0 0.0%	1 0.1%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	809 98.8%

Fig. 3 Confusion Matrix for Quadratic SVM (SNR=10dB)

two different groups of modulation schemes. The C2 is trained with 4-ASK, 32-APSK, 64-APSK and 16-QAM while the C3 is trained with 16-APSK, 128-APSK and 64-QAM. The flow of the hierarchical classification is illustrated in Figure 4.

The group of modulation schemes with which the second stage classifiers are trained is identified based on the evaluation of confusion matrices and mentioned in the previous section in detail. The modulation types classified in the first (C1) and second stages (C2 and C3) are shown in Figure 5.

It should be noted that 4 classes (M-APSK where M=64, 128 and M-QAM where M=16, 64) are highly confused. Then, one of the classifiers (C3) could be trained with 128-APSK while the other (C2) is trained with 32-APSK and 64-APSK schemes. In this way, modulation schemes that are highly confused can be classified with high accuracy. For instance, the classification accuracy for 128-APSK is increased from 48.4% to 92% after 5dB. This similar approach could be applied to M-QAM (where M=16,64), 4-ASK and M-APSK (where M=16,64). Then, the modulation classes are grouped accordingly. For instance, 64-APSK is highly confused with 128-APSK, and then 64-APSK is trained with C2. On the other hand, 16-APSK and 128-APSK are trained with C3 since their constellations are similar to 64-APSK. When the 64-APSK signal will be given to both classifiers for testing, it can be successfully classified in

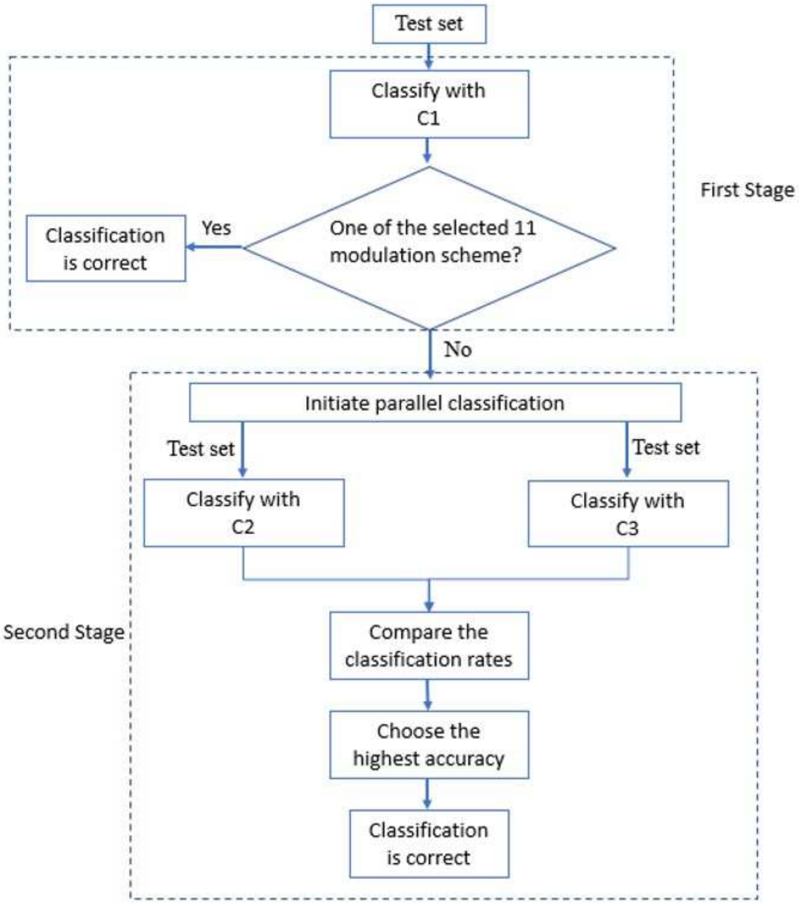


Fig. 4 Flow of the Proposed Hierarchical Classification Model

C2 with a high rate, while in C3, confusing between 16-APSK and 128-APSK and resulting in a low classification rate. In the end, when the classification rates of the classifiers are considered as their weighted votes, 64-APSK will be correctly classified in C2 with a high rate.

In Figure 6, the comparison of the performances of the traditional (Trad) classification and the hierarchical (Hier) classification model for 4-ASK, M-APSK (with M=16,64,128), and M-QAM (with M=16,64) modulation schemes are shown. It should be noted that the proposed hierarchical classifier provides a significant improvement for each of the modulation schemes with a short training time (approximately less than 3 hours).

Figure 7 shows the comparison of the overall classification accuracies for traditional and the proposed hierarchical classifier. The classification accuracy is increased from 85% to 95%, on average, by using the proposed hierarchical classifier structure.

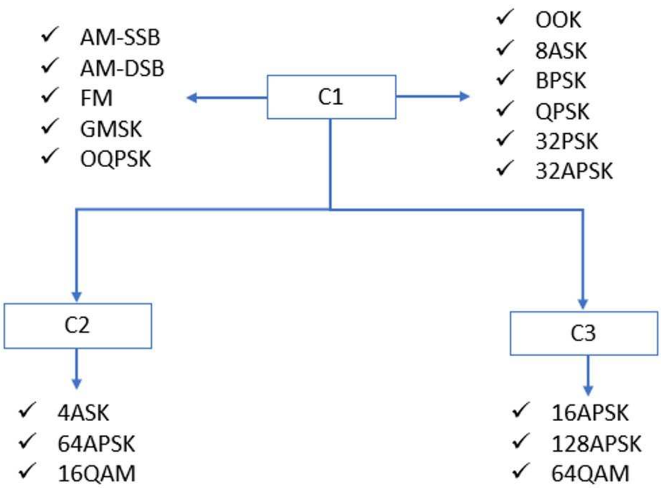


Fig. 5 Grouping of Classes in the Hierarchical Classification Model

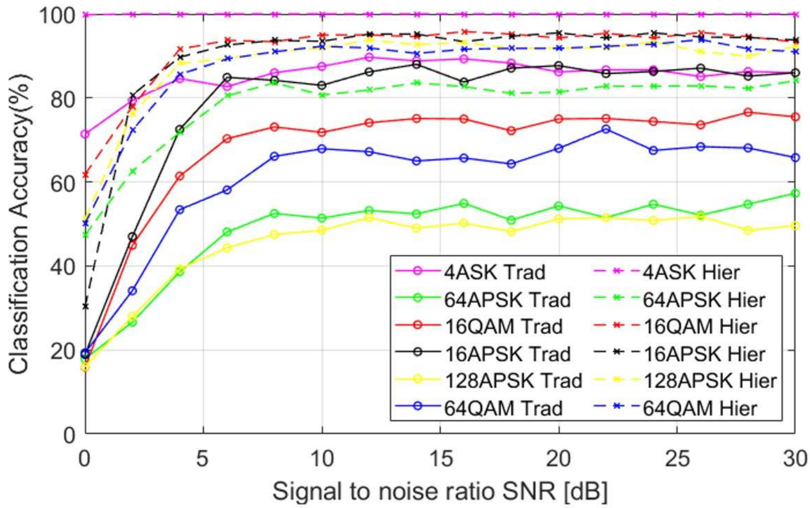


Fig. 6 Performances of Traditional (Trad) and Hiercarchical (Hier) classsification models

Finally, a high-level overview of the methods and their classification performances in the literature are presented in Table 2 along with the proposed work. When the publications in the table are examined, it can be concluded that

- Some consider either only low order modulation schemes [14, 16, 26, 37, 41, 45] or limited number of modulation schemes [5, 10, 12, 14, 18, 26, 41].
- Some [11, 16, 18, 26, 34, 41, 45, 54] use synthetic channel effects with computer generated data rather than OTA.

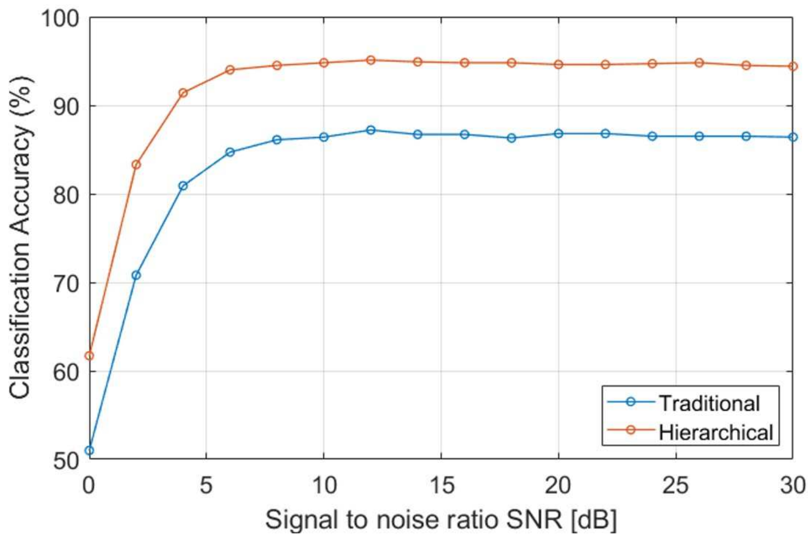


Fig. 7 Comparison of overall accuracy

- Hierarchical based classifications [11, 21, 37, 41, 45] generally achieve 90-100% accuracy at high SNR values (i.e. >10 dB) but only for limited number of modulation classes, and/or under the synthetically simulated channel effects i.e. AWGN. Also, when the SNR level drops, accuracy decreases dramatically.
- In general, high performances are achieved only for limited number of modulation schemes, at high SNR values (10 dB) compared with our work (5 dB).

4 Conclusions and Future Work

This study presents an improved classifier structure for automatic classification of wide range of modulation schemes including SSB, DSB and FM as well as OOK, M-ASK, M-PSK, M-QAM and M-APSK (up to the order of 128). The proposed hierarchical classifier structure is based on the confusions and constellations of respective modulation schemes, in particular, higher-order modulation schemes when the traditional classifier is utilized. Some well-known classifiers are also evaluated initially for choosing the most appropriate classifier for use in the proposed hierarchical classifier structure. The feature set consists of HOS (a vector of 41 features).

It should be noted that the classification performance is highly dependent on the constellation structure of the modulation types. Higher the modulation order, more complex the constellation diagram which makes the classification more difficult. One way to handle this is to use a simple hierarchical classification model based on the modulation type and then the order. However, this requires many classifier stages. This leads to high complexity as well as time

Table 2 Comparison of Classification Performances

Ref.	Dataset (Modulation Types)	Method (Classifier/Features)	Acc. (%)	SNR (dB)
[5]	BPSK,QPSK,8PSK,16QAM,64QAM	Blind modulation classification, ALRT	∼85	5
[10]	BPSK,QPSK,8PSK,16QAM,64QAM (multipath fading-real propagation)	CSS-SVM,MR-CSS-SVM,frequency offset	∼80	5
[11]	M-PSK(2,4,8),M-QAM(16,64,256) (AWGN-slow flat fading-computer generated)	Hierarchical polynomial classifier, cumulants	86.52	5
[12]	QPSK,16QAM,64QAM (OTA signals)	Deep neural network Random forest Decision tree	95 93 90	10
[14]	2FSK,4FSK,8FSK,QPSK,BPSK(UWA-non-cooperation underwater acoustic communication signals)	ANN, spectral features	∼93	10
[16]	2ASK,2FSK,2PSK,4ASK,4FSK,4PSK, 16QAM,MSK,OQPSK(AWGN-computer generated)	SVM fuzzy network, wavelet packet transform modulus maxima matrix	∼99	5
[18]	BPSK,QPSK,8PSK,16QAM,64QAM (computer generated fading channel)	SVM-C40,C41,C42,C63 features	56.40	5
[21]	FSK,2ASK,4ASK,8ASK,QPSK,8PSK, 16QAM,64QAM	Naive SVM Hierarchical-local density	97.29 98.65 100	16
[26]	2FSK,4FSK,8FSK(computer generated)	K-means clustering,spectral centroid feature	100	10
[34]	BPSK,QPSK,8PSK,4QAM,16QAM, 64QAM(multipath fading,computer-generated)	Quadratic SVM-moment,cumulant	97.2	5
[37]	BPSK,QPSK,OQPSK,QPSK,MSK, 16QAM(fading channel,real propagation)	Blind modulation classification, hierarchical hypothesis test	∼96	10
[41]	BPSK,PAM,QAM,8PSK (AWGN,computer generated)	Hierarchical classification, cumulant-based	70	5
[45]	2ASK, 4ASK,8ASK,BPSK,QPSK, 8PSK(AWGN-computer generated)	Hierarchical,decision tree,higher-order cumulants	96	10
[54]	4ASK,8ASK,2PSK,4PSK,8PSK,Star-8QAM,V29,32QAM,64QAM (AWGN,computer generated)	Hierarchical SVM, higher order moments and cumulants	96	3
This work	OOK,4ASK,8ASK,M-PSK(2,4,32),M-APSK(16,32,64,128),M-QAM(16,64),SSBSC,DSBSC, FM,GMSK,OQPSK(OTA signals)	Hierarchical SVM, HOSs	95	5

consumption and impracticability. Also, when the literature is examined, the number of modulation types to be classified is limited and the channel effects are not realistic in general.

The hierarchical classification model proposed in this study resolve this complexity and time consumption with two basic stages and achieves high accuracy (>95% at 5 dB or more) for wide range of modulation types, from basic analog modulations to higher-order digital modulations. As a future work, by extending the dataset size and modulation classes, the classification structure can be improved.

Declarations

- Funding - The authors declare that no funds, grants, or other support were received during the preparation of this manuscript.

- Conflict of interest/Competing interests - The authors have no relevant financial or non-financial interests to disclose. The authors declare that they have no conflict of interest.
- Ethics approval - The manuscript has not been submitted or published anywhere.
- Consent to participate - Not applicable.
- Consent for publication - Not applicable.
- Availability of data - The datasets analyzed during the current study are available in https://www.deepsig.ai/datasets?hsLang=en.
- Code availability - The code generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

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