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Exploratory Feature Analysis for Deep Learning based Spectrum Sensing

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***Abstract*—In the present work, a feature based deep learning spectrum sensing model is developed wherein the features are extracted from the received radio signals captured using GNU Radio. The efficacy of proposed model does not depend on the *a priori* knowledge of the signal structure. The data set used to develop the model supports multiple modulation techniques, reasonable range of signal to noise ratio with embedded noise and interference. The dependency of the features selected and extracted are investigated using deep learning (DL) based classi- fier which learns the hidden class distribution of the signal based on the labelled data. A deep convolutional neural net (CNN) is designed to attain acceptable classification accuracy. In addition, the proposed deep CNN model is tested against various other state of the art machine learning (ML) models and conventional model to prove its efficacy. From the results, it is evident that the proposed model outperforms the other models in most of the cases.**

***Index Terms*— Cognitive Radio (CR), Spectrum Sensing (SS), Deep Learning (DL), Convolutional Neural Net (CNN), Feature Extraction.**

I. INTRODUCTION

The current research on 5G networks [1], the rapid growth of the Internet of Things [2], and development of other new and modern technologies, relies heavily on the use of wireless spectrum. In this regard, *cognitive radio* (CR) plays an important role in improving the efficiency of using the available spectrum optimally utilizing the spectrum resources [3]. *Spectrum Sensing* (SS) is the key to attain dynamic spec- trum allocation in CR [4], [5]. Researchers are still actively developing and proposing new algorithms on SS to improve the efficacy of the scheme. Generally, SS techniques involve designing of the decision statistic to detect the presence of *primary user* (PU) signal by deploying some stochastic method to the data i.e. received signal. Therefore, it is very essential to design the decision statistics properly for acceptable SSperformance. The presence or absence of PU is decided by comparing the decision statistic with pre-determined or esti- mated threshold. Thus, SS, in essence, is a binary classification problem.
The energy detection (ED) method in spectrum sensing relies on assessing the energy of received signals to detect the presence or absence of primary users (PU) [6]. Additionally, features like pilot tones (PT) [7], cyclic prefix (CP) [8], and covariance matrix (CM) [9] of received OFDM signals are utilized. However, these methods depend on modeling noise uncertainty, carrier frequency offset (CFO), or synchronization errors, and require prior knowledge of PU signals such as CP or PT structure and noise power [10], [11]. These strict requirements hinder fast decision-making in modern wireless networks, making conventional

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sensing techniques inadequate for evolving communication networks.

Deep learning (DL)-based spectrum sensing (SS) methods are gaining traction as they offer a learnable parametric approach compared to the estimated parametric techniques of traditional methods. These DL methods involve learning in- trinsic signal features or signal class from given features [12]– [15]. Unlike conventional techniques, DL-based SS eliminates the need for calculating a statistical decision statistic [15]– [17]. Research suggests DL methods outperform traditional approaches and are agnostic to modulation types, reducing receiver complexity [18]–[20].

Cooperative spectrum sensing (CSS) has primarily captured attention in DL-based SS, where DL combines individual sensing results from multiple *secondary users* (SUs) for decision-making [14], [21]–[23]. However, non-cooperative SS works are emerging as well [15], [24], [25]. Two main categories of DL-based SS approaches are evident: one trains a DL network to learn signal features, which are then input into another DL network for classification [24], [26], [27]; the other calculates features using numerical techniques or probabilistic models, then feeds them into a DL network [28]– [30]. This work focuses on the latter approach, proposing a non-cooperative spectrum sensing method using DL that leverages the underlying features of received signals.

The proposed work extracts features from received signals without prior knowledge of signal structure. These features are investigated for their dependency and used to train a deep learning (DL) based classifier on labeled data. A deep *convo- lutional neural network* (CNN) achieves high classification ac- curacy. The proposed model is compared against various *state of the art* machine learning (ML) models and conventional methods, consistently outperforming them. Testing accuracy of the model is detailed in the results section.

A. Scope and Contribution

The scope of this paper is to develop, analyse and compare the performance of the proposed DL based SS model in terms of probability of detection (P_d) and receiver operating char- acteristics (ROC) under noisy and fading channel conditions with features as inputs to the model. At first, different features are calculated from the received signal and used in learning the parameters of the model. This in turn reduces the model complexity, training time while enhancing the efficacy. The inter-dependency of the features are also investigated in order to study the effect of the salient features on the performance of the model. Simulation results reported here also prove the superiority of the proposed model over other conventional as well as DL based models.

The major contributions of the proposed work are:

- Exploiting different features in the received signal in place of only one to enhance the performance of the model.
- Investigating partial dependency among the features to reduce redundancy.
- Using a simple yet robust DL based model for classifi- cation purpose.
- Deploying a reduced parameterized model to minimize training time and model complexity.

II. RELATED WORKS

Conventionally, SS schemes incorporate methods such as energy detection [31], [32], cyclostationary feature-based de- tection [33], [34], eigenvalue-based detection [35], frequency domain entropy-based detection [36], and power spectral den- sity split cancellation-based method [37]. Energy detection is widely used but affected by noise uncertainty [3]. Cyclosta- tionary feature-based detection works in low SNR but is com- putationally complex and needs signal knowledge. Eigenvalue- based detection is robust but resource-intensive. Frequency domain entropy-based methods differentiate noise and signal distributions. Power spectral density split cancellation-based methods require sparse monitoring frequency bands. Non- conventional techniques like ML are being explored to over- come limitations.

ML techniques in spectrum sensing are predominantly ap- plied in cooperative spectrum sensing (CSS). In one study [38], authors proposed an ML-based CSS classifier to address channel and receiver uncertainties, utilizing received complex signals as feature vectors. Another study [39], employed a support vector machine (SVM) for multi-class classification based on quantified signal energy in absence of primary user (PU) signals. A CNN-based collaborative sensing method was introduced to enhance performance and reduce compu- tational complexity [18]. Additionally, a federated learning- based model was presented to manage data overload, using sample covariance matrices as input features [40]. Feature selection is crucial in ML-based CSS for reduced data di- mensionality, intrinsic signal structure, and minimal training time.

Recent research focuses on ML-based single node spectrum sensing (SS). A proposed deep learning signal detector ex- ploits structural information of modulated signals without prior knowledge of channel state or noise

[41]. Another study [42], employs ANN with autocorrelation features. Cyclostationary features and power spectral densities enhance CNN-based SS [43]. Stacked autoencoders are also used to learn hidden features for OFDM signal detection [44]. Furthermore, transfer learning-based deep CNN enables non-cooperative SS in TV bands using power spectral density [15].

The foregoing discussion evidently shows the importance of selection of features on the performance of ML based non- cooperative SS model. The present work focuses on enhancing the performance of the proposed ML based SS classifier model by suitably choosing input features. The mutual independence of the selected features are also investigated and ensured through simulation results. Furthermore, the performance of the proposed model is shown to have outcompeted other traditional and ML based models.

III. PROPOSED METHOD AND MATHEMATICAL PRELIMINARIES

The problem of SS can be formulated as a binary classifi- cation problem:

$$H0 : \ y(n) = \omega(n) \qquad (1)$$

$$H1 : \ y(n) = x(n) + \omega(n) \qquad (2)$$

where, y(n), x(n) and ω(n) for n = 0, 1,...,M is the nth sample of the received signal, PU signal and AWGN signal at the receiver, respectively, and M is the total number of sensing samples in one observation. The null hypothesis, H0, indicates the absence of PU and the alyernate hypothesis, H1, indicates the presence of PU. Essentially, the proposed deep CNN model acts like a classifier, which categorizes the received signal into two classes. However, the classification task is carried out by learning about the received signal from the feature set. Fig. 1 shows the structure of the data driven SS workflow.

The features extracted from the received signal (dataset) are fed to the CNN model to train and to test the model. Fig. 1 also shows the internal structure of the CNN model. It is evident that feature based PU detection reduces the model complexity and thereby training time. The two convolution layers are used to learn the functional mapping of the signal from the feature space to the output space. To incorporate the non - linearities among class boundaries "*relu*" is used as an activation function in all of the convolution layers. Only the output layer consists of "*softmax*" activation function. The reason for this is that the during training "*one-hot encoding*" is used as labeled output. However, "*sigmoid*" can also be used as an activation function. The next section desribes data preprocessing and partioning for effective learning of the proposed CNN model.

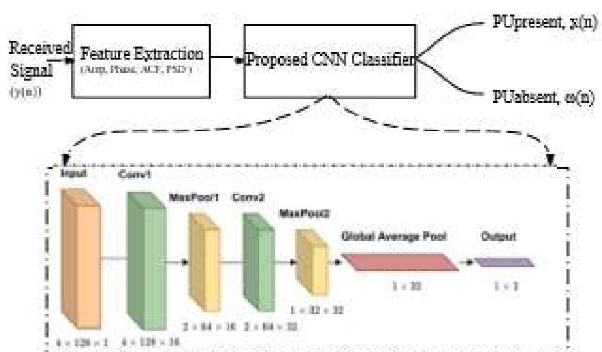

Fig. 1. Proposed System Model

A. Dataset Description and Preparation

For the present work a widely popular baseline dataset "RadioML 2016.10A" is used, which consists of synthetically generated radio signals captured using GNU Radio. The di- mension of the dataset is Nmod × NSNR × Nsamples × 2 × Nsignal length, where Nmod is the total number of modula- tion types used for NSNR range. Furthermore, for a given SNR, Nsamples of complex OFDM signal having a length of Nsignal length is generated. The 2 in the above expression represents *In phase* (I) and *Quadrature* (Q) components of the signal. In the present work, 5 modulation type is considered, i.e. Nmod = 5. Thus the dimension of dataset used in the proposed work is 5 × NSNR × Nsamples × 2 × Nsignal length. The signals under positive values of SNRs are assumed to consist of PU + noise signal, whereas the signals under negative SNRs are AWGN noises.

Instead of directly using the time domain complex signal from the dataset, it is pre-processed to extract features that would in turn help the classifier to learn quickly. The fol- llowing features are considered i) amplitude

(A), ii) phase (Φ), iii) autocorrelation fumction (ACF) and iv) power spec- tral density (PSD). Thus, if F is the feature vector, then

F = [f A, f Φ, f ACF , f PSD]T , where, f ∈ R4×N signal length

$$f^{A_i} = \sqrt{a_i^2 + b_i^2} \quad (3)$$
(4)
$$f^{\Phi_i} = \arctan\,(b_i/a_i) \quad (4)$$
$$\mathbf{f}^{ACF} = E\{\mathbf{y}(n+\tau/2)\mathbf{y}^*(n-\tau/2)\} \quad (5)$$
$$\mathbf{f}^{PSD} = |\mathcal{F}(\mathbf{f}^{ACF})| \quad (6)$$

where, i = 1, 2,...,Nsignal length, ai and bi are the coeffi- cients of the received complex OFDM signal (y(n)), E(.) is Each of the features is calculated as follows,-
the expectation operator, τ is the lag and F (.) is the *Fourier* transform. As every feature is calculated for one sample for each SNR and a given modulation type, hence the dimension
of F ∈ $R^{Nmod \times NSNR \times Nsample \times 4 \times Nsignal\ length}$. One example of features extracted from each modulation type at SNR = 0 dB is given in Fig. 2. From Fig. 2 it is evident that features belonging to a particular type of modulation scheme are starkly different from each other which in turn help the proposed classifier learn efficiently. Further exploration of the feature matrix is done in the following section.

TABLE I. TRAINING PARAMETERS AND ACTIVATION FUNCTION

Layer Type	Activation	Parameters
Convolution	ReLU	160
MaxPooling	-	0
Convolution	ReLU	4640
MaxPooling	-	0
Global Average Pooling	-	0
Dense	SoftMax	66

IV. SIMULATION RESULTS AND DISCUSSION

This section presents the performance of the proposed method through simulation results. As discussed before, the choice of features plays an important role in the efficacy of the classifier model. Further investigations are carried out in order to find the impact of the chosen features and the correlation among them, on the classification accuracy. The correlation map among the features is shown in Fig. 3. It is evident from the figure that most of the selected features are highly uncorrelated, however, a partial correlation exists between ”ACF” and ”Phase”. Although, all the features show almost no correlation with the ”Target” varible. It is worth to mention that highly correlated features are redundant and they impact the performance of a classifier model negatively [13]. The partial dependence between features affects the performance of the model and hence, experiments are conducted using the same dataset to observe the marginal effect of one or two features have on the predicted outcome the proposed model. If the feature is not correlated with the other features, then the partial dependancy represent how the feature influences the prediction. In the uncorrelated case, the partial dependence shows how the average prediction changes when one of the feature is changed. Fig. 4 shows that the chosen features are completely independent of each other. This, in turn, enhance the performance of the proposed classifier in terms of accuracy, training time and overfitting [12].
Simulation results are shown here for the digitally modu- lated signal mapping based OFDM transmitted signal. A *Look- up* table is prepared to keep track of the modulation type and SNR variation under each modulation scheme. Furthermore, the dataset is reshaped before presenting it at the input of the percentage of hypothesis H has occured. The complete set of parameters and activation functions are given in Table I. The classification accuracy of the proposed model for test data is shown in Fig. 6. The proposed classifier model classifies the signal with negative values of SNR as ω(n) and signal with positive values of SNR as x(n)+ ω(n). Even when the values of SNR is within the range of -5 to 5 dB, the classifier is able to correctly identify the presence of PU. This shows the efficacy of the proposed model. The proposed model is also tested against conventional as well

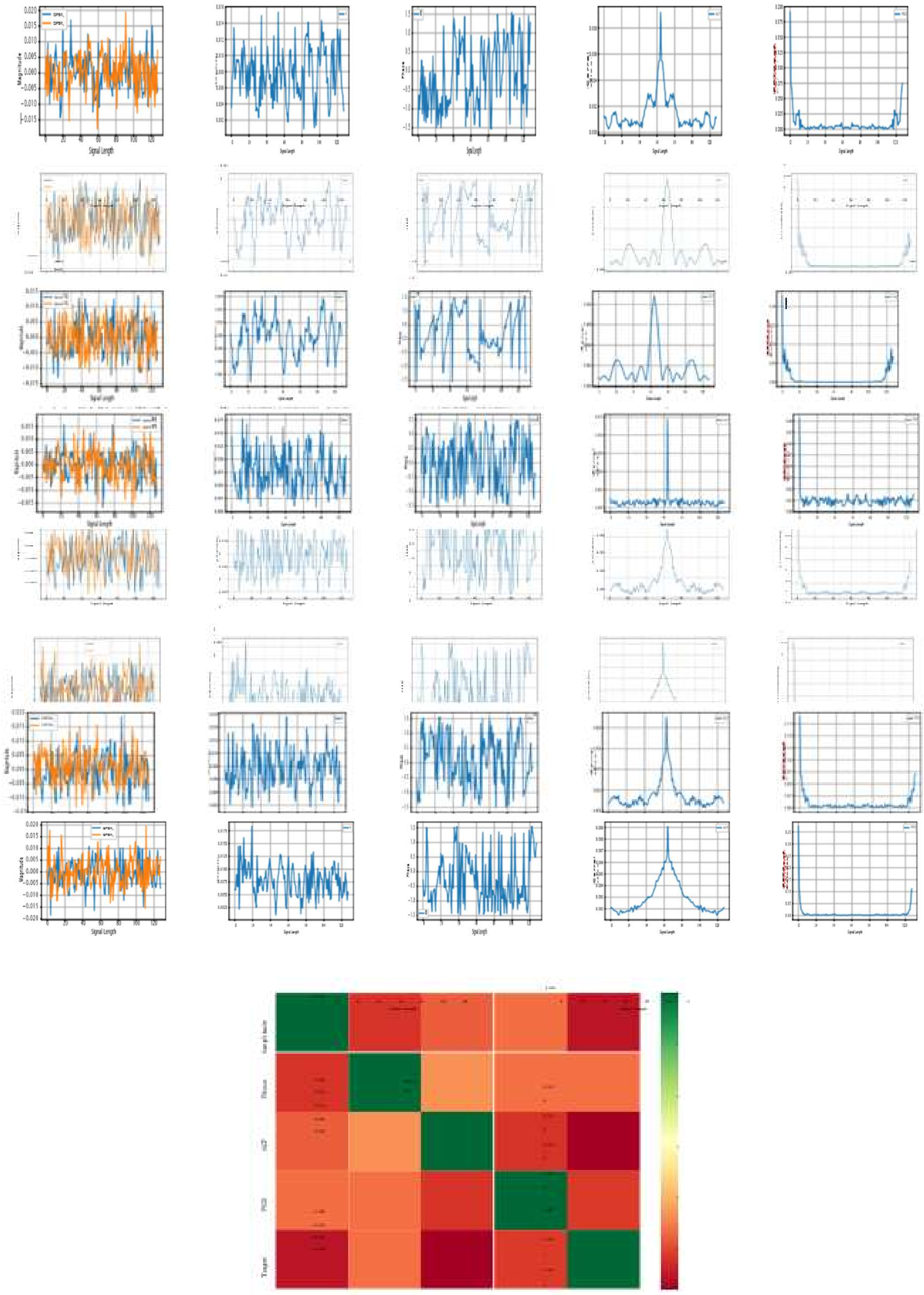

Fig. 2. Modulation type and extracted features at SNR = 0 dB (from left to right: In phase and Quadrature component, Amplitude, Phase, ACF, PSD)

conventional as well as ML based *state of the art* models is obtained in terms of the Receiver Operating Characteristics (ROC) and Pd versus SNR curves. The Pd ans values are obtained by calculating the ratio of the accurately proposed CNN structure. Hence, the new dimension of the dataset is 100000×4×128×1. Now the dataset is partitioned into training, testing dataset in 70:30 ratio, keeping equal 0 1 in each ofthe dataset. The network is trained for 100 epochs and result of training and validation losses are shown in Fig. 5. It is also evident from the graph that no "overfitting" or "underfitting" predicted H1 class to the total number of classes at each SNR from the test dataset. As evident from Fig. 7, the performance of the model is almost same in the low SNR region, however, in the high SNR region the proposed model outperforms the other models in terms of detection efficiency. It is worth to mention that the trained classifier acts as the *Neyman-Pearson* detector, popularly used for signal detection.

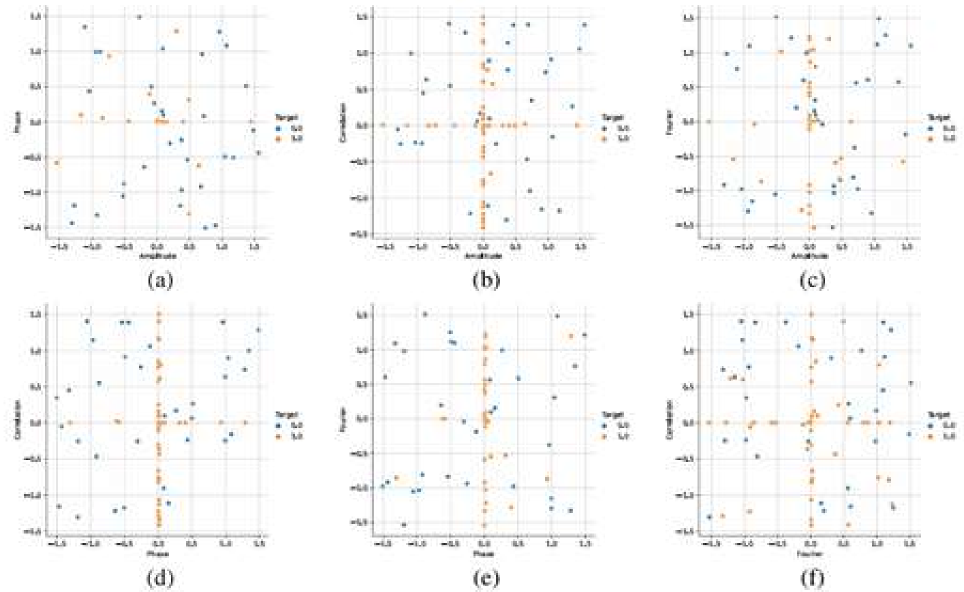

Fig. 4. Correlation among different features: (a) Phase vs. Amplitude, (b) ACF vs. Amplitude, (c) PSD vs. Amplitude, (d) ACF vs. Phase, (e) PSD vs. Phase, (f) PSD vs. ACF

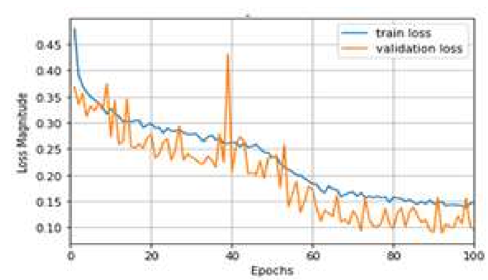

Fig 5. Training and Validation Loss

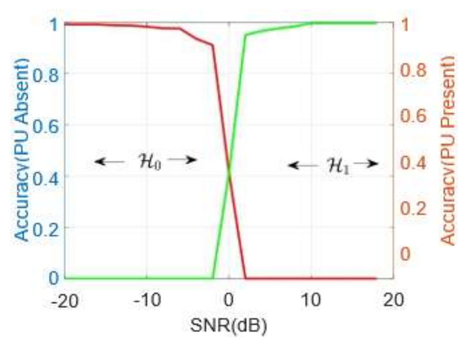

Fig. 6. Classification accuracy

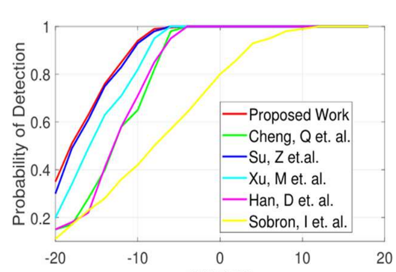

Fig. 7. Detection Performance: Probability of Detection (Pd) vs. SNR

V. Conclusions

The present work proposes a feature based DL-SS classifier model for efficient detection of presence or absence of PU. The model is found to have shown significant performance improvement over the conventional energy detector. Although, the model is trained and tested on a popular dataset ("Ra- dioML 2016.10A"), it can be used for real world dataset by following the same procedure. Furthermore, the dataset used for training the model is made modulation insensitive, therefore, the proposed model has shown generalization ability to similar modulation schemes. In addition, simulation results reported here also proves the superiority of the proposed model over other *state-of-the-art* DL based models. In future, a feature based stacked classifier approach can be considered to further enhance the detection efficiency. It is worth to mention here that the present work considers only single PU and single SU, further studies can be made on a more generic scenarios e.g., multiple PUs and multiple SUs.

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