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Title **WIRELESS SPECTRUM DETECTION USING DEEP LEARNING FOR WIRELESS COMMUNICATION**

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Wireless Spectrum Detection using Deep learning for Wireless Communication

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Abstract:
The main focus of this article is Spectrum sensing for efficient data transfer in wireless communications. Currently, there is a need for an effective wireless communication system because the serviceable spectrum is not sufficient due to exponential growth in the number of wireless device users. One approach for effectively using the spectrum is through Radio frequency sensing. Spectrum-aware radio relies on Radio frequency sensing to detect available spectrum for better usage and to reduce harmful interference with licensed users. For spectrum sensing, there are currently established techniques based on energy detection, but the development of machine learning has made spectrum sensing more efficient. A machine learning-based model can perform better than traditional methods. To identify the existence of a licensed user, we suggest a machine learning spectrum sensing technique employing a Convolutional Neural Network model in a Gaussian environment. Such that if the spectrum is not being utilized by the licensed user then the secondary user can benefit from it. This methodology will be very helpful in resolving the spectrum scarcity problem in wireless communications.

Key Words: *Spectrum sensing, Spectrum utilization, Energy detection, CNN.*

INTRODUCTION:

Wireless networks are now widely used and considered essential in today's life due to the rapid development growth of its user base and range of applications [1]. The increasing demand for radio spectrum is beyond the capabilities of the present spectral management model is to keep up. To reduce this shortage, a variety of spectrum reuse solutions have been proposed. By enabling unlicensed users opportunistic access to the spectrum, it is possible to address the issue of spectrum utilization with the help of Spectrum-aware radio [2].

According to the research that has been done, Cognitive Radio has many more benefits than only better spectrum management. When it comes to the spectrum shortage, Cognitive Radio was the premier solution to address the problem of spectrum scarcity because of its many benefits, including enhanced throughput and novel services in radio equipment and higher spectral efficiency [3].

Cognitive radio technology is an interesting strategy for solving the problem of underutilized wireless spectrum. Cognitive radio can adapt the settings of its transmitter to the conditions in which it is operating [4]. Cognitive radios are developed to promote efficient use of the radio spectrum and to ensure that all users of the network have access to highly reliable communication capabilities at all times. Spectral sensing, Spectral management, Spectral sharing, and Spectral mobility are the four cornerstones of cognitive radio's architecture. The purpose of spectrum sensing is to identify authorized users and obtain information about available frequencies [5]. Spectrum sharing is the process of allocating scarce radio frequencies among competing users in a cost-effective manner. The goal of spectrum mobility is to keep communications running smoothly even when they are upgraded to a higher quality frequency range [3].

Literature Survey

Among all the studies, convolutional neural networks (CNNs) have emerged as the clear frontrunner. Studies by Captain [5] et al. discussed the most popular Radio frequency sensing methods which are energy disclosure and matched disclosure and they found that Receiver Operating Characteristic curves are being created by representing either detection chance versus false alarm probability. Given a bell-shaped distribution with zero mean and one standard deviation. Studies by Lee [7] et al. discussed about cooperative Radio frequency sensing in a reinforcement learning method and they found that Conventional CSS techniques perform worse than DCS, especially in challenging sensing environments. Further the run time of DCS is larger than those of conventional methods. It can be improved by decreasing the computation time.

SPECTRUM SENSING:

Radio signal detection in a specific frequency range is known as spectrum sensing. In dynamic spectrum access systems, where wireless devices can opportunistically access unused frequency bands, this technique is extremely important for facilitating optimal use of spectrum resources [1]. Spectrum sensing can be used in the context of data transfer to identify channels with sufficient bandwidth. Primary transmitter detection is used to describe the process of identifying the existence or vacancy of a primary transmitter signal in a particular frequency band [6]. Spectrum sensing can be accomplished by a variety of designs, namely cyclostationary feature identification, and compressive sensing. Different methods have different complexity levels, precision levels, and computational needs [3]. Particularly in cases where spectrum resources are scarce or otherwise congested, spectrum sensing plays a crucial role in ensuring efficient and reliable data transmission via wireless networks. Since models based on machine learning to outperform more traditional approaches, that are increasingly being used to improve results. To identify licensed user, we come up with a Convolutional Neural Network model operating in a Gaussian environment for spectrum sensing [4].

PROPOSED MODEL

As a subset of Deep Learning architecture Convolutional Neural Networks (CNNs) are frequently employed in image classification and recognition applications. It has several layers such as filter layers, down sampling layers and dense layers. The convolutional layer employs kernels on the input feature in order to extract features. During training, a Conv layer employs a set of learnable filters to the input feature and produces a set of feature maps.

1. Input Layer: Here, we feed information into our model at the input layer. Our data contains a total of n characteristics, therefore n neurons were present in this layer.

2. Hidden Layer: It consists of multiple convolutional and pooling layers. The convolution layers apply a set of learnable filters to the input feature, and build a set of feature maps. The pooling layer diminishes the structural dimensions of the feature maps and the output of the last hidden layer is unrolled and given to fully connected layers and the turnout of this layer is fed into sigmoid layer.

3. Output Layer: To determine the probability score for each class, a logistic function like sigmoid is applied to the output of the latent layer.

Next stage is, feed forward, involves supplying the model with data in order to

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obtain the layer-by-layer output. Then, we use an error function to calculate the error. Then, we back produce the model after computing variables. In general Back propagation is the process that is used to reduce waste. In this article swish activation function with lecun uniform and lecun normal kernel initializers have been proposed, and in the final stage for classification purpose sigmoid activation has been used with adadelta optimizer.

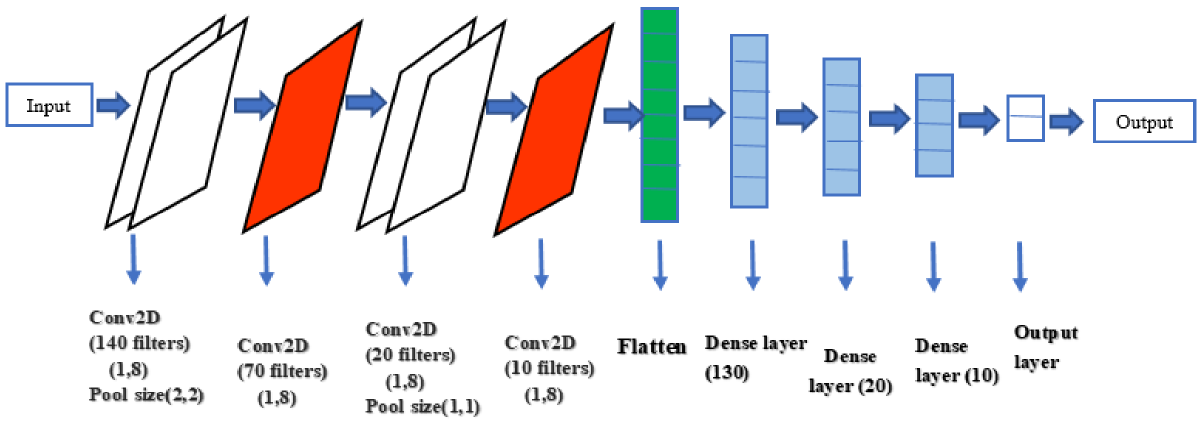

Fig.1Proposed diagram based on CNN

The above diagram illustrates the working of the proposed model. The data set is the input to the convolution layer, which typically represents the pixel matrix of the data. The input layer is fed to 2-dimensional convolutional layer with 140 filters, each of which has size of 1x8 (meaning of filter size is 1 along the vertical dimension and 8 along the horizontal dimension). The pool size (2,2) indicates that after the convolutional operation, a max-pooling operation with a pool size of 2x2 is applied to the output layer of the convolutional layer. Overall, this layer is meant to glean 140 sets of feature sets from the input data, each of which corresponds to a different filter, and then reduce the spatial size of the feature maps through max-pooling. The next layer is the 2 dimensional convolutional layer with 70 filters each of which has size 1x8. This layer is designed to extract 70 sets of features from the input data each of which corresponds to a different filter. The spatial size of the output feature maps from the convolutional layer is already small enough. So there is no need to apply max-pooling to further reduce the size. The next layer is Conv2D which consists of 20 kernels which has size 1x8. The pool size of 1x1 is fed to decision layer of feature extractor. Actually this type of pooling operation doesn't actually perform any pooling or down sampling of the input data. Instead, it simply passes the input data through unchanged. This is fed to Conv2D with 10 kernels which has size 1x8 and there is no max-pooling layer because the size is already reduced. The layer next to the 2 dimensional Convolutional layer is the flatten layer. A conv2d layer is used to extract features and generate 2D feature maps as output. In order to pass this information to fully connected layer that expects 1D input, the feature maps need to be flattened into a vector. It is fed to a dense layer with 130 neurons, it means that the flattened vector is being treated as a 1D input to a fully connected layer with 130 neurons. The flattened vector contains the feature information that has been extracted by the previous layers in the network. Each neuron in the dense layer takes thus input vector and performs matrix multiplication with a weight matrix followed by a bias term, to produce an output value. The weights and biases in the layer are learned through backpropogation

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during training. It is fed to a dense layer with 20 neurons and then fed to a dense layer with 10 neurons. The purpose of adding another dense layer in this way is to further process the extracted feature information from the previous layers and to provide more opportunities for the network to learn high-level representations of the input data. It improve its ability to make accurate predictions on new data. Finally the dense layer with 10 neurons is fed to the output layer which consists of one or more neurons depending on the specific task. For multi-class classification the output layer may consist of multiple neurons, each representing a different class, with a sigmoid activation function to produce a probability distribution over the 2 classes. For developing this architecture model in this article deepsig dataset that is radioml 2016.04.C has been considered and was downloaded from the following RF datasets for Machine Learning website: https://www.deepsig.ai/datasets. Overall the result of the network's computation on the input data and can be used for a variety of tasks, including prediction, classification, and regression. The output of the network may be scalar or vector representing the predicted numerical value or values.

RESULTS

Here the performance of a classification model on a dataset with binary labels can be summarized using various metrics, including TP, TN, FP, FN, accuracy, precision, recall. These metrics are typically presented in a Table 1.

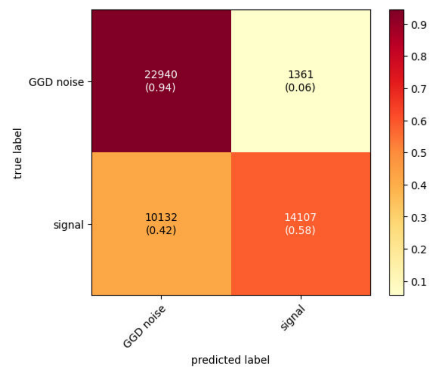

Fig. 2 Confusion Matrix

		True Condition			
	Total Population	**Condition Positive**	**Condition Negative**	**Prevalence**	
Predicted Condition	**Prediction Positive**	**True Pos (TP)** 1361	**False Pos (FP) (type 1 error)** 1361	**Precision Pos Predictive value** 0.912	**False Discovery Rate** 0.087
	Prediction Negative	**False Neg (FN) (type 2 error)** 10132	**True Neg (TN)** 22940	**False Omission Rate** 0.306	**Negative Predictive Value** 0.69
	Accuracy 0.763	**Sensitivity (SN), Recall, Total Pos Rate** 0.58	**Fall-Out, False Positive Rate FPR** 0.056	**Pos Likelihood Ratio LR+** 10.35	**Diagnostic Odds Ratio DOR** 4.6
		Miss Rate, False Neg Rate FNR 0.418	**Specificity (SPC), True Neg Rate** 0.943	**Neg Likelihood ratio LR-** 2.25	

Table.1 Calculations for Confusion Matrix

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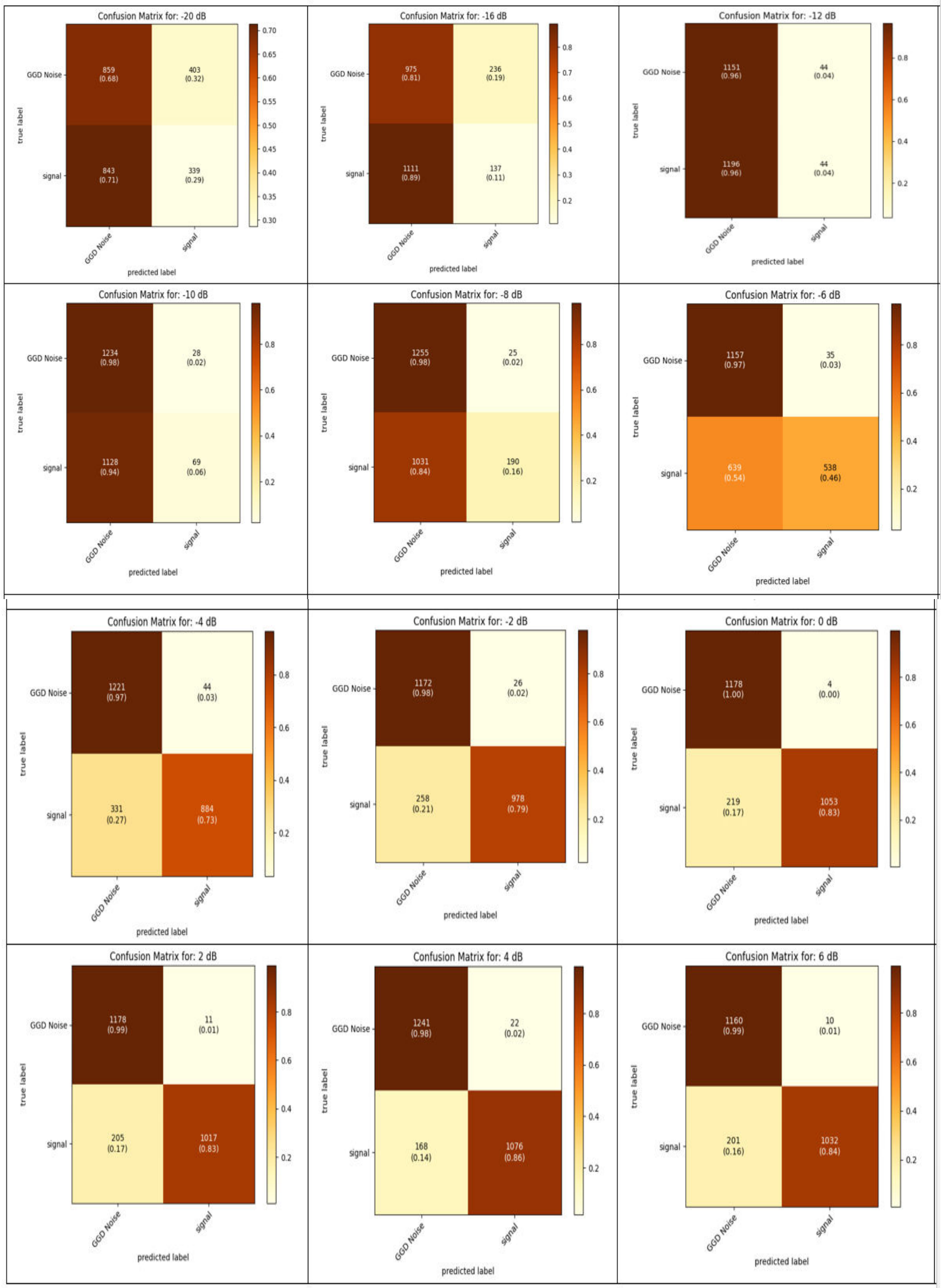

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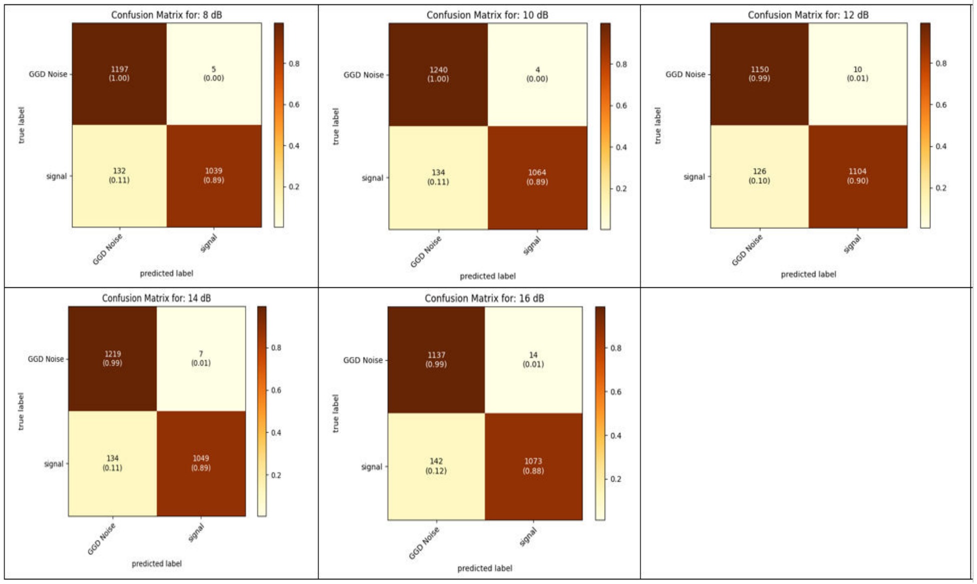

Fig. 3 Confusion matrix values for -20 dB to 16 dB

We summarize the performance of a model on classification task of detecting a signal in the presence of noise based on Table 1. The positive class corresponds to positive class and negative class corresponds to the absence of signal. Here the model has an accuracy of 0.76, indicating that it correctly that it correctly predicts the class of 76% of the samples in the test set represents in Table 1.

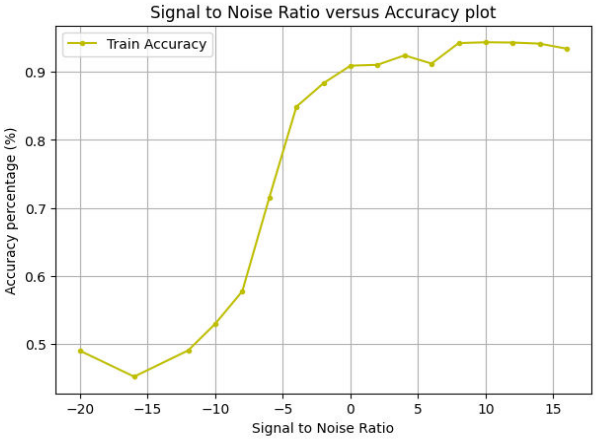

Fig. 4 Accuracy vs SNR

CONCLUSION

Spectrum management issues have surfaced recently because of the expansion in wireless network users versus the availability of spectrum. In this article we used machine learning models to assign the spectrum to users in an efficient manner, which necessitates a strong and reliable means of declaring the spectrum to be unused. In this case, TP, TN, FP and FN metrics used to determine whether or not a channel was free. The positive class represents the target condition while the negative class represents the nonoccurrence of that condition. When the channel strength is positive, it means the channel's licensed user is actively engaged. If it is negative then it indicates that the channel was not utilized by licensed user. So allocation of channel can be done to unlicensed users if channel is not used.

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REFERENCES

[1] Chen, Zhibo, et al. "Deep STFT-CNN for spectrum sensing in cognitive radio" in IEEE Communications Letters 25.3, 2020.
[2] Deyu Zhang, Zhigang Chen, Haibo Zhou, "Energy Harvesting-Aided Spectrum Sensing and Data Transmission in Heterogeneous Cognitive Radio Sensor Network", IEEE Publications, 2015.
[3] C. Liu, J. Wang, X. Liu, and Y. C. Liang, "Deep CM-CNN for spectrum sensing in cognitive radio", IEEE Journal on selected Areas in Communications, 2019.
[4] Manse Subhedhar and Gajanan Birajdur, "Spectrum Sensing Techniques In Cognitive Radio Networks: A Survey", International Journal of Next-Generation Networks, 2011.
[5] Captain, Kamal M., and Manjunath V. Joshi. "Spectrum Sensing for Cognitive Radio: Fundamentals and Applications" in CRC Press, 2022.
[6] Liu, Chang, et al. "Deep CM-CNN for spectrum sensing in cognitive radio" in IEEE Journal on Selected Areas in Communications 37.10 (2019).
[7] Lee, Woongsup, Minho Kim, and Dong-Ho Cho. "Deep cooperative sensing: Cooperative spectrum sensing based on convolutional neural networks" in IEEE Transactions on Vehicular Technology 68.3, 2019.
[8] Zheng, Shilian, et al. "Spectrum sensing based on deep learning classification for cognitive radios" in China communications 17.2. 2020.
[9] A. Mehrabian, M. Sabbaghian and H. Yanikomeroglu, "CNN-based for spectrum sensing with General Noise Models", in IEEE Transactions on Wireless Communications, 2022.
[10] T. Yucek and H. Arslan, "A survey of spectrum sensing algorithms for cognitive radio applications", IEEE Communications Surveys Tutorials, 2009.
[11] X. Zhu, T. Wanf, Y. Bao, F. Hu and S. Li, "Signal detection in generalized Gaussian distribution noise with nakagami fading channel", IEEE Access, 2019.
[12] E. Axel and E. G. Larsson, "Optimal and sub-optimal spectrum sensing of OFDM signals in known and unknown noise variance", IEEE Journal on Selected Areas in Communications, 2011.
[13] B. Soni, D. K. Patel, and M. Lpez-Bentez, "Long short-term memory based spectrum sensing scheme for cognitive radio using primary activity statistics", IEEE Access, 2020.
[14] M. Bkassiny, Y. Li and S. K. Jayaweera, "A Survey on Machine-Learning Techniques in Cognitive Radios", in IEEE Communications Surveys and Tutorials, 2013.
[15] Xie, Jiandong, "Deep learning-based spectrum sensing in cognitive radio: A CNN LSTM approach", IEEE Communications Letters, 2020.