Optimizing Cognitive Radio Networks with Deep Learning-Based Semantic Spectrum Sensing

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Abstract — Spectrum aggregation in 4G and 5G networks is a technique used to combine multiple frequency bands to boost communication performance. The cognitive radio feature improves the ability to combine spectrum in LTE and 5G environments by enabling dynamic spectrum sensing. Spectrum sensing is a major problem in spectrum aggregation due to the presence of various types of interference, such as noise. Phase noise is an issue due to its 1 MHz frequency offset experienced within 5G's 28 GHz operating band, with the distorted signal generating more spectrum sensing-related errors. To solve this problem, the proposed work suggests an optimized deep learning-based semantic spectrum sensing model using three sets of optimizers (ResNet-50, DeepLab V3 and sand cat) offering a high detection accuracy of 99.7% with the optimized training parameter of a high signal-to-noise ratio equaling 40 dB.

Keywords — cognitive radio, ResNet-50, sand cat optimizer, semantic spectrum sensing, wireless sensor network

1. Introduction

A wireless communication transceiver using the cognitive radio (CR) concept identifies and utilizes unused radio channels to make the best use of the available spectrum. This technique has been used to minimize interference and improve the quality of service. In the United States, the Federal Communications Commission (FCC) and the National Telecommunications and Information Administration (NITA) allocate the limited wireless RF spectrum to licensed users – an approach that results in overcrowding or underutilization of the spectra. Consequently, spectrum inefficiencies are experienced, leading to reduced data transmission rates and lower service quality levels.

CR networks are classified into two types: primary and secondary. A primary network consists of licensed users and radio transmitters, while a secondary network shares the unused spectrum with the primary network. Identification of channel occupancy in CR increases spectrum efficiency and minimizes interference. It is achieved by spectrum sensing – a technique allowing to determine whether specific frequency bands are used or not.

Cognitive radio networks detect the presence of primary users within specific frequency bands, allowing secondary users to access the spectrum without creating any interference [1]. In cognitive radio spectrum sensing, holes are defined as periods in which primary-user signals are not detected, thus allowing secondary users to access a given frequency band.

Two spectrum access modes may be distinguished: overlay and underlay. When principal users are not transmitting, secondary users utilize the spectrum in the overlay mode. Therefore, efficient spectrum access is required in the overlay mode to avoid interference from primary users [2]. In the underlay mode, a secondary user transmits a signal simultaneously with a primary user, and the secondary user must adjust its transmit power accordingly, taking account the interference caused by the primary user [3].

Cognitive radio (CR) is a fundamental element of 4G/5G communication systems. It enables multiple wireless and mobile networks to operate efficiently, improves their performance by utilizing the unlicensed spectrum, provides improved coverage in rural areas by using overlay and underlay spectrum access techniques, and facilitates the use of higher frequency bands, such as millimeter wave bands, in 5G wireless communication [4].

Despite the increasing adoption of 5G seen in many countries, coexistence of 4G and 5G networks is still quite common due to the time required to build new telecommunications infrastructure and the widespread availability of 4G networks. 5G networks are well suited for high data rates and low latency applications. However, many rural areas still lack 5G coverage, necessitating the continued use of both networks during the transition period.

Spectrum aggregation (also known as carrier agreement) allows several frequency bands to be combined into a single channel to boost data rate, network capacity and, hence, network performance. Spectrum aggregation enables network operators to allocate the capacity of radio cells operating at different frequencies, thus enhancing the end-user experience.

Spectrum aggregation, introduced in 3G networks, was limited to a 5 MHz bandwidth per carrier. In 4G LTE, each carrier is aggregated with a 20 MHz bandwidth. However, in 5G networks, carrier aggregation is supported at low- and mid-frequencies (below 7 GHz), as well as at high-band millimeter frequencies (above 24 GHz). In 5G, each carrier operates with a bandwidth of 100 MHz, being five times wider than in 3G [5].

Dynamic spectrum sharing between 4G LTE and 5G radio signals is the main issue with spectrum aggregation. In spectrum sharing, 4G users cannot transfer carriers from LTE to 4G due to spectrum aggregation [6].

Phase noise is another problem that reduces performance. During the spectrum aggregation process, noise reduces sensitivity, thus increasing the noise floor, and lowers the quality of the aggregated spectrum. furthermore, it is challenging to discriminate between distinct frequency channels in a local receiver due to phase noise. Phase noise can also lead to signal degradation and distortion, making it difficult to have a steady and reliable connection during spectrum aggregation. Therefore, reducing phase noise is essential to increase the efficacy and efficiency of communication systems.

The wireless communication industry is currently adopting technology that uses mmWave frequencies, thus making higher data speeds possible. To lower the bit error rate, faster data rates require a higher signal-to-noise ratio. Therefore, the proposed work implements an optimized deep learning semantic spectrum localization approach to estimate the phase noise in order to increase the quality of the aggregated spectrum. By measuring and adjusting phase noise, the proposed deep learning semantic spectrum localization technique facilitates data transmission and reception in 4G LTE and 5G networks.

The rest of the article is structured as follows.

Section 2 offers a review of spectrum aggregation, noise interference and spectrum sensing phenomena associated with CR. Section 3 describes the proposed methodology. The results are presented and discussed in Section 4. Conclusions are given in Section 5.

2. Literature Review

Over the years, researchers have proposed many spectrum aggregation techniques, including the multi-agent long- and short-term (LSTM)-based deep Q-learning architecture (DQN) as a solution to the distributed dynamic spectrum access issue experienced in temporal correlations involving primary and secondary users [7]. For the effective detection of spectrum gaps, the author [8] employed a spectrum detection algorithm based on spiking neural networks (SNN) trained with the modified whale optimization algorithm (MWOA).

Another spectrum aggregation technique was employed in [9] to detect unlicensed users to facilitate the efficient transmission of smart agriculture technologies. Using spectrum aggregation technology, the maximum entropy actor-critic (MEAC) algorithm was presented in [10], allowing secondary users to share the spectrum. It was discovered, with the use of the spectrum aggregation technology, that the MEAC algorithm allowed secondary users to effectively share the spectrum resources. The SNN-based spectrum sensing method trained on MWOA has shown efficacy in identifying spectrum gaps, thus enhancing spectrum accessibility for primary and secondary users.

In the face of noise uncertainty, the authors of [11] detected the unoccupied primary bands using the estimator-correlator-based optimum detectors and the generalized likelihood ratio test (GLRT) paradigm.

To identify the principal user, paper [12] relied on a primary key cryptosystem. The secondary user provided the error correction key which was used to eliminate noise while assigning resources to the secondary user. When sensing the spectrum, Kendall's tau detector finds the main signal in the additive non-Gaussian noise that is described by the contaminated Gaussian model (CGM).

In [13], the eigenvalue-based random matrix theory (RMT) is used for multidimensional cognitive radio receivers to find correlation noise caused by oversampling and filtration errors. The bivariate isotropic symmetric α-stable (BISαS) model presented in [14] was used by the author to identify non-Gaussian impulsive noise in spectrum detection. By employing a radial basis function network, article [15] resolved the issue of an increased rate of misclassification in the detection of spectrum, based on time series data.

In [16], a highly efficient spectral network is presented, employing the frequency division multiplexing technique described in the physical layer, while in [17], three unique deep learning models, including convolutional neural networks, recurrent neural networks, and neural networks are employed to determine the spectrum of the secondary user (SU). These models were employed to detect the spectrum in a 5G network. A large data set was used to train these models to precisely determine spectrum occupancy. The results demonstrated that deep learning models outperform conventional spectrum sensing techniques, offering a much higher accuracy rate and generating fewer errors.

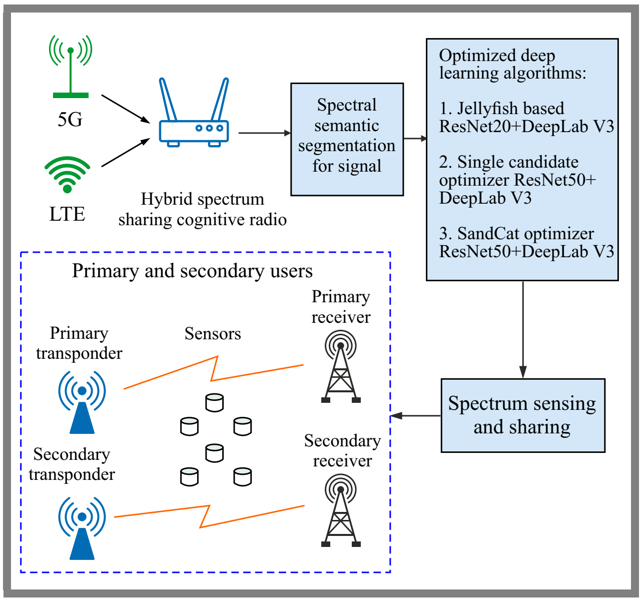

Fig. 1. Proposed architecture for spectrum aggregation in optimized deep learning-based semantic segmentation network.

3. Proposed Methodology

The proposed architecture of spectrum sensing in spectrum aggregation using the semantic segmentation technique is

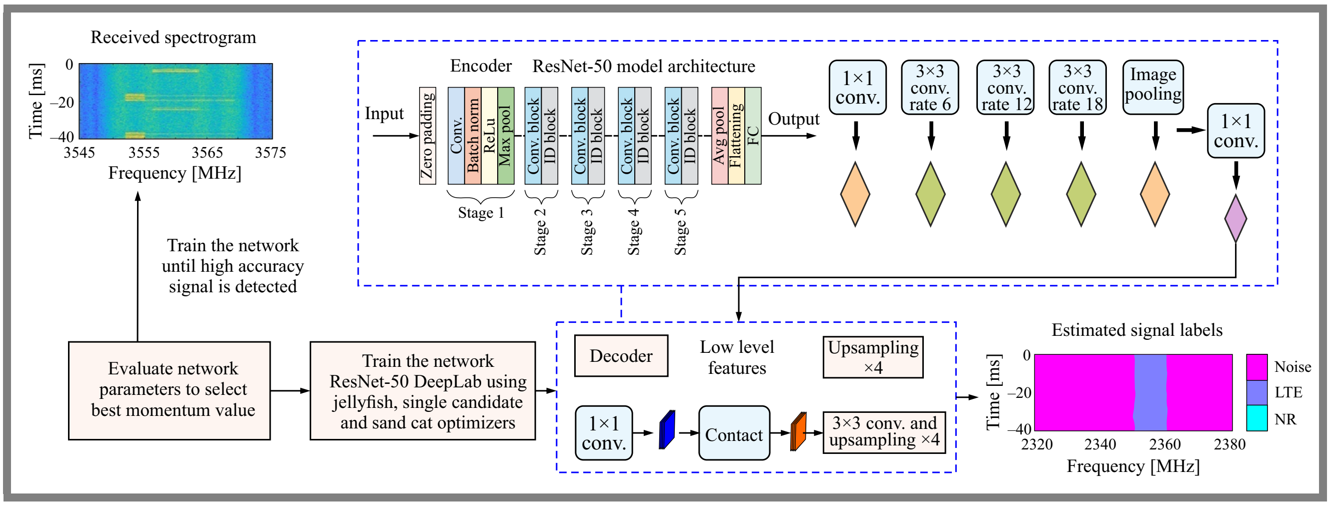

Fig. 2. Block diagram of the proposed ResNet-50 and DeepLab V3 semantic segmentation spectrum network.

shown in Fig. 1. Spectrum sensing is performed in spectrum sharing environments using an optimized deep learning model of a cognitive radio network. 5G and 4G LTE signals are generated with a sampling rate of 61.44 MHz, with an image size of 256 by 256, with each frame lasting 10 ms.

The frequency of each signal is analyzed and segmented into different classes, such as LTE, 5G, and phase noise signals based on spectral characteristics, using an optimized deep learning model. After semantic segmentation, the spectrum signals are allocated to primary and secondary users based on their requirements for the shared spectrum signal. This allocation process ensures efficient utilization of the spectrum resources, allowing primary users to have priority access, with secondary users being allowed to access the remaining part of the spectrum. Additionally, by detecting and decreasing phase noise, the overall quality of the shared spectrum signal is improved for both primary and secondary users.

3.1. Semantic Spectrum Segmentation

Semantic spectrum segmentation is a technique that is used to identify the spectrum based on the high-level features of the signal. Semantic spectrum segmentation in CR (SSS-CR) employs dynamic spectrum access for underutilized spectrum bands and enables context-aware spectrum usage. SSS in CR improves spectrum sharing between primary and secondary users while minimizing interference and optimizing spectrum allocation.

The proposed work employs LTE and 5G NR interfaces that detect the presence of phase noise using the deep learning approach. The presence of phase noise is classified by the semantic segmentation method and optimizes spectrum sensing.

3.2. ResNet-50 Based Deep Semantic Segmentation Network

Semantic segmentation (SS) is used to classify pixels that belong to a particular class. SS is used to combine pixels of the same class and supports multiclass segmentation. The proposed work uses ResNet-50 as a backbone network with DeepLab V3 to segment signals in cognitive radio, such as 5G, LTE and phase noise signals. ResNet-50 comprises 4 stages of layers, such as the initial stage, containing convolution, and the maximum pooling layer, followed by 3 sets of residual blocks. Thanks to the convolutional module, the skip connection feature and accurate pixel detection, ResNet-50 is capable of obtaining information about pixels that are inside a spectrogram signal. Therefore, the model is suitable for extracting such features as frequency content, frequency bands, spectral density, time frequency location, and spectral peaks from the spectrogram.

DeepLab V3 uses an arbitrary convolution network and a spatial feature pyramid to acquire multiscale features without adding more parameters to the proposed architecture. The DeepLab V3 architecture uses an encoder and decoder. The encoder encodes finer details of the spectrogram, while the decoder is used to obtain the desired resolution. In DeepLab V3, dilation rates are used to capture multiscale features which regulate the space between kernel weights and the receptive field.

The training parameters for stochastic gradient descent with a momentum algorithm is optimized using jellyfish, single candidate, and sand cat optimizer algorithms to increase the performance of the proposed ResNet-50 and DeepLab V3 network. Optimization strategies improving speed and accuracy are chosen as well.

Figure 2 shows the proposed architecture of the semantic segmentation network.

3.3. Jellyfish Optimization

Jellyfish is a bio-inspired optimization algorithm implemented based on the food search habits of jellyfish. The algorithm finds the best location where the most food is available. While the lookout for food, jellyfish are carried by the ocean current or move in a swarm. We used the jellyfish optimization algorithm to optimize the momentum training parameter

Algorithm 1 Jellyfish-based semantic spectrum sensing

Initialize parameters and variables, number of population, number of dimensions, lower and upper bound for momentum, and maximum iteration
Initialize population using logistic map initialization technique and set lower bound and upper bound to vectors
Evaluate the initial population using the cost function
Initialize the best solution `BestSol` and its corresponding cost `BestCost`
for each iteration until the maximum iteration is reached **do**
    Calculate the mean of the current population `Meanvl`
    Sort the population based on costs
    for each solution in the population **do**
        Calculate the time control factor A_r
        if $A_r \geqslant 0.5$ **then**
            Update the solution by following the ocean current method and update the new position of jellyfish
        else
            Determine the type of motion (active or passive)
        end if
    end for
end for
Output the optimal momentum value u and its corresponding cost f_{val}

based on the condition of a high mean accuracy value in deep learning semantic spectrum segmentation.

The momentum training parameter is essential to enhance the convergence speed and stability of deep learning models. Using the jellyfish optimization algorithm, we can effectively search for the optimal value of this parameter, leading to enhanced performance in semantic spectrum segmentation tasks. Algorithm 1 illustrates the pseudocode of jellyfish optimization.

3.4. Single Candidate Optimization

The single candidate optimizer (SCO) supports the entire optimization process to find the best solution. The evaluation process depends on the maximum number of function evaluations or iterations involved. The process is divided into two phases, and candidates update their positions in each phase. The Algorithm 2 evaluates the cost function in semantic spectrum sensing to optimize the momentum training parameter and updates the position of a candidate based on the current mean accuracy value. Additionally, by dividing the optimization into two phases, the algorithm can adapt and refine its search strategy based on the results obtained in each phase.

3.5. Sand Cat Optimization

The sand cat swarm optimization method (SCSO) was implemented based on the behavior of sand cats. The SCSO algorithm simulates sand cats' hunting techniques, allowing them to successfully locate and capture prey. Using this

Algorithm 2 SCO-based semantic spectrum sensing

Initialize parameters: lower bound for momentum, upper bound for momentum, number of dimensions, cost function for optimization, number of iterations
Initialize a random candidate solution within the specified limits
Evaluate the best fitness of the initial candidate solution `BF` using the cost function f_{obj}
Set the initial values for counters and parameters
for each iteration t from 1 to T **do**
    Calculate the inertia weight
    Update counters and check if in the second phase
    Generate a new candidate solution and determine the motion strategy based on the current phase
    if $t < \alpha$ **then**
        Determine the motion strategy for the first phase
    else
        Determine the motion strategy for the second phase
    end if
    Enforce boundary constraints on the new candidate solution
    Evaluate the fitness $F(t)$ of the newly generated candidate solution
    if $F(t)$ is better than the current best fitness **then**
        Update the best solution and its fitness
    end if
    Store the `BF` for the current iteration t in `BF`(T)
end for
Output the optimal momentum value $gbest$ and its corresponding cost `BF`(T)

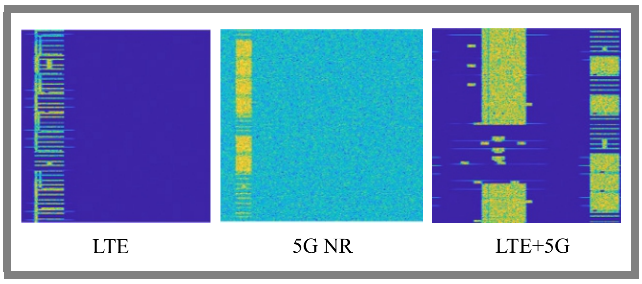

Fig. 3. LTE and 5G NR generated signal samples.

behavior during the optimization process, the SCSO algorithm performs better at detecting and tracking low-frequency noises that could be food sources. As a result, modifying the momentum training parameter with the SCSO technique is an effective method to improve overall performance. Algorithm 3 shows the pseudocode of SCSO.

4. Results and Discussions

The data set for the simulation is generated for 5G and LTE signals with added phase noise of the specified bandwidth. More detailed data from case A relate to urban areas, and less detailed data from case B to rural areas. Sub-carrier spacing between 15 and 30 kHz and synchronization of a single block

Algorithm 3 SCSO pseudocode

```
Initialize parameters: number of search agents SearchAgents-no, maximum iterations max-iter, lower bound and upper bound for each dimension, number of dimensions, and cost function for optimization
Initialize the best score BS to positive infinity and the best fitness BF to an array of zeros with length equal to dim
Initialize the positions of search agents (positions) using the initialization function
Initialize the convergence curve array to zeros with length equal to max-iter
if number of values = 1 then
    assign initial condition
else
    set the iteration counter t to 0
end if
while t < max-iter do
    for each search agent i from 1 to SearchAgents-no do
        Evaluate the fitness of the current position using the cost function f_obj
        if the current fitness is better than BS then
            update BS and BF
        end if
    end for
    Update the maximum sensitivity range S and the guide range r_g
    for each search agent i from 1 to SearchAgents-no do
        Generate a random value r between 0 and r_g
        Generate a random value R between -r_g and r_g
        for each dimension j from 1 to dim do
            Calculate the transition phase angle θ using the RouletteWheelSelection function
            if R satisfies the motion strategy condition then
                Select a random search agent cp and update the position of dimension j
            end if
        end for
        Enforce boundary constraints on the updated position of dimension j
    end for

    Increment the iteration counter t
    Update the convergence curve array with the current BS
end while
Output the best score BS, the best fitness BF, and the convergence curve array (convergence-curve)
```

period of 40 ms are used as well. LTE signals are created using R.2, R.6, R.8 and R.9 reference channels for downlink transmissions in cities or in indoor environments, with low or high interference levels and a frequency division duplex (FDD). Table 1 shows the parameters used in the simulation, whereas Fig. 3 shows the sample signals.

Tab. 1. Parameters used for the generation of the signal data set.

Parameter	Value	Units
5G NR		
Bandwidth	10, 15, 20, 25, 30, 40, 50	MHz
Subcarrier spacing	15, 30	kHz
SSB block pattern	case A, case B	
SSB period	20	ms
LTE		
Reference channel	R.2, R.6, R.8, R.9	
Bandwidth	5, 10, 15, 20	MHz
Duplex mode	FDD	
Phase noise		
SNR	0 40	dB
Carrier frequency	2.5	kHz

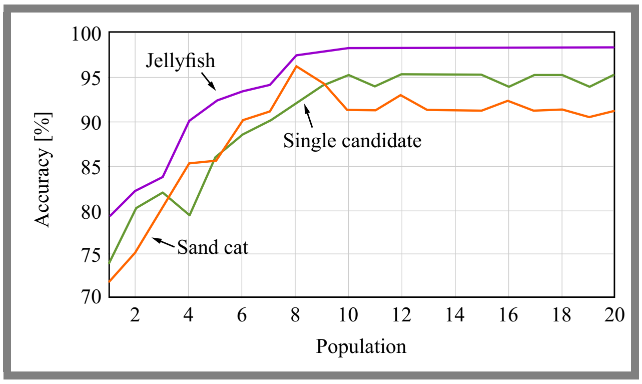

Fig. 4. Accuracy of three considered optimizers.

4.1. Training Parameters Based on Optimized Algorithms

Figure 4 shows the cost values of various spectrum sensing optimization strategies, including jellyfish, single candidate solution, and sand cat. According to the graph, the sand cat algorithm outperforms other optimization strategies in terms of accuracy, and with momentum of 0.9 because the algorithm locates and forecasts accuracy even in low noise environments. As a result, the algorithm classifies the semantic signal with an excellent accuracy level of 98.3%.

Figure 5 shows the degree of precision of the three optimizers under consideration, with respect to 5G, LTE, and phase noise. One may conclude from the figure that the dominance of phase noise is higher than 5G and LTE.

Figure 6 illustrates the sensitivity values of optimizers for 5G, LTE, and phase noise cases, while Fig. 7 provides specific values. One may observe from Fig. 6 that sensitivity to phase noise is lower than in 5G and LTE, and Fig. 7 shows that the sand cat optimizer exhibits faster convergence and greater generalization capabilities, making it an excellent alternative for semantic spectrum deep learning classification problems.

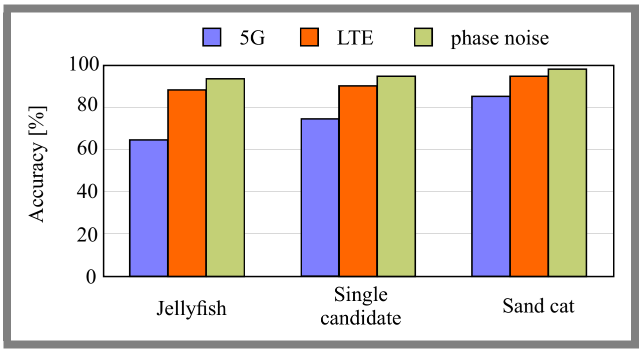

Fig. 5. Accuracy for various classifier models.

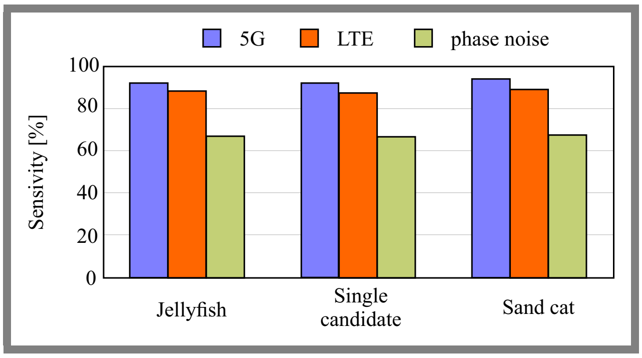

Fig. 6. Sensitivity for three considered classifier models.

These data also demonstrate that the sand cat optimizer outperforms other methods across a wide range of assessment measures.

4.2. Performance Analysis Using ResNet-50 and DeepLab V3

To assess the decrease in the presence of phase noise, all considered optimization classifiers are trained with ResNet-50 and DeepLab V3 (Fig. 8). Figure 9a shows the performance of the optimized ResNet-50 semantic spectrum sensing approach, in terms of global accuracy. It is evident that the captured spectrum sensing for the proposed sand cat optimizer is high when compared with other optimizers. Figure 9b shows the mean captured spectrum sensing accuracy value, with the sand cat optimizer producing a better result compared with other optimizers. Figure 9c proves that the mean spectrum sensing IOU of the sand cat optimizer is high versus the remaining approaches. Fig. 9d shows that the weighted spectrum sensing IOU of the sand cat optimizer is the highest. Figure 9e shows the ResNet-50 BF score that has the highest captured spectrum detection value for the sand cat optimizer, and Fig. 9f presents the F1 score that has a greater captured spectrum detection value for the sand cat optimizer, compared to the ResNet-50 optimizer.

In general, the performance analysis proves that the captured spectrum sensing becomes higher when phase noise is decreased, which enhances the effective utilization of semantic spectrum sensing – see Fig. 10 and Tab. 2.

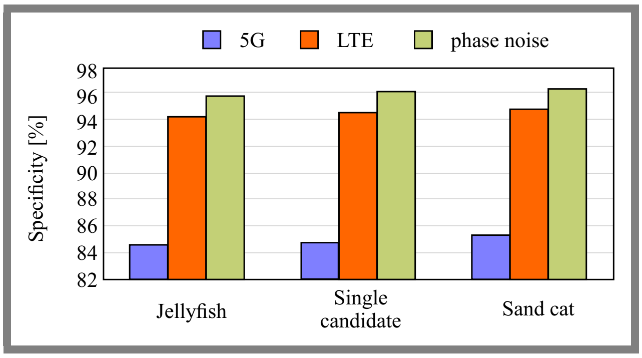

Fig. 7. Specificity for three classifier models.

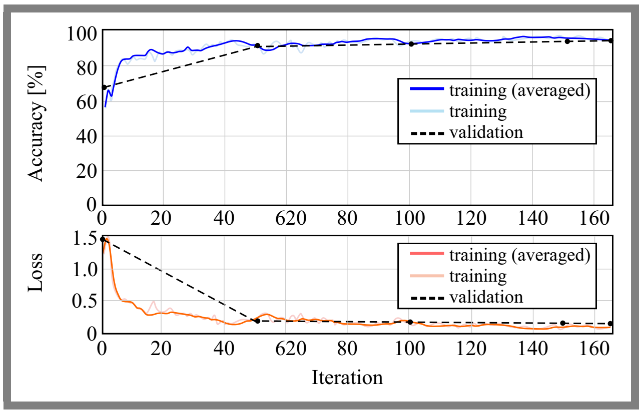

Fig. 8. Training and validation of optimized ResNet-50 and DeepLab V3.

Tab. 2. Comparison of spectrum sensing methods.

Spectrum sensing	Accuracy
ResNet 152 [18]	90.55%
SenseNet [19]	91.25%
DetectNet+SVM [20]	89%
1DCNN+BiLSTM+SA [21]	92%
VGG [22]	95%
Proposed ResNet-50 + DeepLab V3	99.7%

5. Conclusion

The proposed phase noise detection technique minimizes interference, improves signal quality, enhances network capacity and augments spectral efficiency. Unfortunately, the proposed model requires significant amounts of computing power, is sensitive to parameter tuning, and the spectrum characteristics may be subject to change depending on the real-time environment. However, the model provides good results in terms of phase detection and labelling. Therefore, additional research and development work is required to optimize the model for practical deployment in dynamic and unpredictable scenarios. Additionally, the efficacy in changing signal environments will require constant observation and parameter modification.

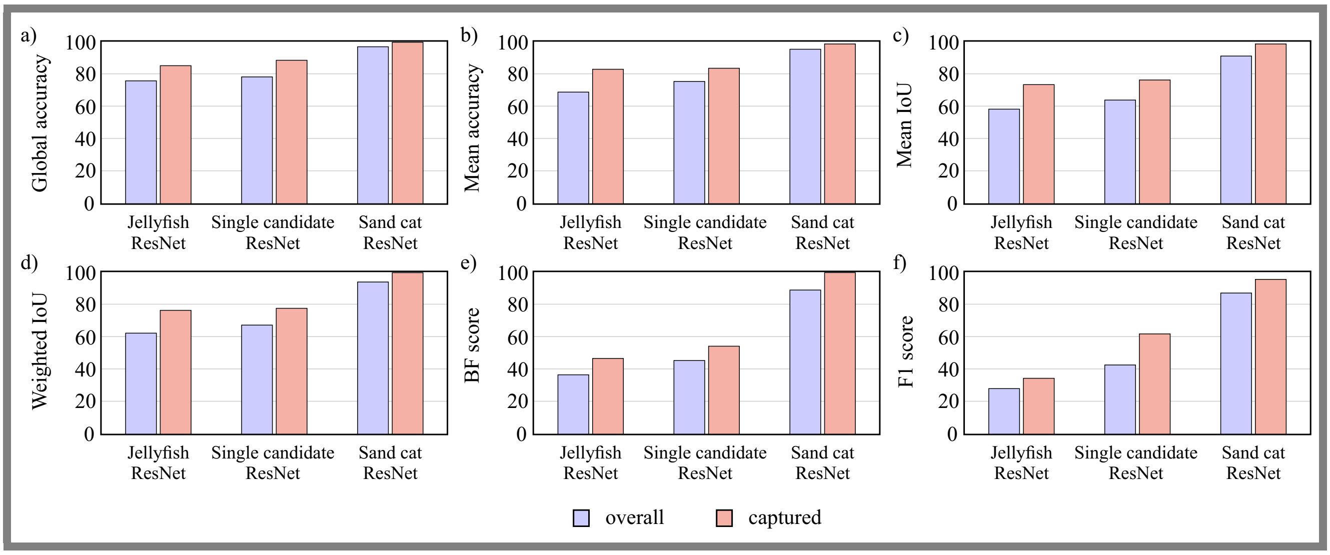

Fig. 9. Performance analysis of optimized ResNet-50 semantic spectrum sensing approach: a) global accuracy, b) mean accuracy, c) mean IoU, d) weighted IoU, e) BF score, and f) F1 score.

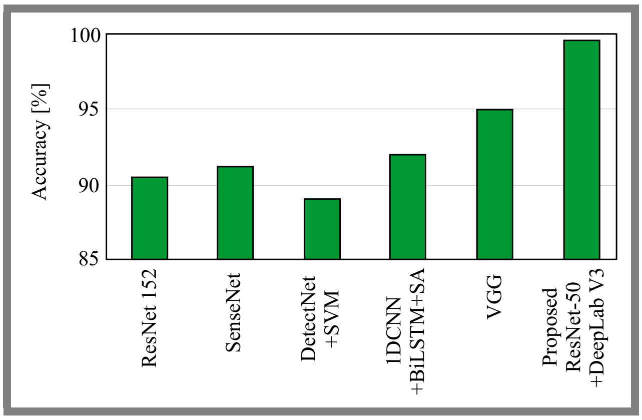

Fig. 10. Comparison of spectrum sensing methods.

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