Evaluation of Spectral Traffic Classifiers in Cognitive Radio Networks Using Deep Learning and Machine Learning

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***Abstract*—Cognitive Radio (CR) technology enhances spectrum efficiency by enabling unlicensed users to utilize underused frequency bands opportunistically. This work introduces a methodology that integrates deep learning-based feature extraction with classification techniques grounded in machine learning to enhance decision-making within Cognitive Radio Networks (CRNs). Spectral characteristics are derived from image representations of power distribution and subsequently categorized using four classifiers: Binary Decision Tree (BDT), Discriminant Analysis Classifier (DAC), K-Nearest Neighbors (KNNC), and Support Vector Machines (SVM). The study's main contribution lies in validating the applicability of deep neural networks for spectral classification and assessing the influence of each classification model on decision-making outcomes. Performance is measured through total and failed handoffs, average bandwidth, and overall delay. Findings indicate that the SVM classifier achieves superior accuracy and operational efficiency. The SVM classifier performed best, recording the fewest handoffs and the lowest average delay. Regarding the number of handoffs, BDT, KNNC, and DAC increased this metric by 1.44, 1.88, and 2.88 times, respectively, demonstrating the greater efficiency and stability of the SVM classifier. SVM also achieved the best results for the other metrics evaluated.**

***Keywords*—machine learning, feature extraction, spectral handoff, spectral occupancy, cognitive radio networks, decision making**

I. Introduction

According to the Federal Communications Commission, spectrum is severely underutilized, an estimated 80% of allocated spectrum is below potential usage, this means that frequency availability for current users and new users will be a challenging issue [1, 2]. To solve this problem, different strategies have been proposed, CR is a technology that has received great attention from academia and industry. It allows the allocation of the spectrum in a dynamic way; it is composed of licensed or Primary Users (PU) and unlicensed or Secondary Users (SU). In the dynamic model of CR, EDs can opportunistically access when spectrum is available [3].

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To enable dynamic access, Cognitive Radio Networks (CRNs) operate based on a cognitive cycle comprising spectrum sensing, spectrum decision, spectrum mobility, and spectrum sharing [4]. Spectrum decision is crucial, as it depends on accurately and efficiently characterizing the PU signal. The success of decision-making depends on the characteristics of the network; therefore, the permanent work is to identify and propose intelligent learning strategies, which allow the analysis of spectral occupancy in order to estimate the characterization of the PU [5].

A. Scope and Contributions

This article addresses the classification of spectral occupancy as a key element in decision-making within CRNs. To this end, we implement an approach based on feature extraction using deep learning and subsequent classification using machine learning techniques.

Spectral features are obtained from the activations generated in the upper layers of the AlexNet deep neural network, which is used to recognize images associated with spectral power levels. Based on these features, four machine learning-based classification models are trained and evaluated: Binary Decision Tree (BDT), Discriminant Analysis Classifier (DAC), K-Nearest Neighbor Classifier (KNNC), and Support Vector Machines (SVM). The main objective is to identify the most efficient classifier for determining spectral occupancy based on three traffic levels: high, medium, and low.

The results obtained with each technique are transformed into time and frequency information to evaluate the impact of classification on decision-making, allowing the construction of a zone-scoring vector for spectrum access. From this vector, key metrics are generated that quantify the performance of the decision-making process. The metrics analyzed are the cumulative average number of handoffs, the cumulative average number of failed handoffs, the average bandwidth, and the cumulative average delay. These metrics are studied over the SU transmission time, providing a detailed evaluation of the effectiveness of each classifier in dynamic cognitive radio scenarios.

This study validates the viability of deep learning for feature extraction in spectrum occupancy classification and highlights the importance of selecting the appropriate classifier to optimize decision-making in CRNs.

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The results provide valuable information for developing more efficient spectrum management strategies, thus contributing to the advancement of next-generation wireless communication networks.

B. Literature Review

Previous research has explored various machine learning and deep learning applications in CRNs. This paper analyzes studies focused on learning algorithms that can be integrated into CRNs' multiple processes.

Deep learning is a key tool for addressing fundamental challenges in CRNs, including spectrum sensing and sharing, resource allocation, and system security. According to Ref. [6], applying these techniques improves the network's adaptive capacity in dynamic environments, optimizing system efficiency and reliability. Thus, deep learning is emerging as a crucial element in ensuring the performance and security of future wireless infrastructures.

Spectrum availability is a critical factor in CRNs. In this context, Swetha *et al.* [7] explored the use of various machine learning techniques, including Linear Discriminant Analysis (LDA), Logistic Regression (LR), K-Nearest Neighbors (KNNC), Naive Bayes (NB), Classification and Regression Trees (CRT), and Support Vector Machines (SVM), for Primary User (PU) identification. The results show an accuracy of 85%, suggesting the feasibility of these techniques to optimize spectrum sensing and improve spectrum allocation efficiency within CRNs. These findings reinforce the importance of machine learning in next-generation wireless environments.

Intelligent transportation systems based on Vehicular Ad Hoc Networks (VANETs) have demonstrated outstanding potential; however, they still face challenges related to efficient spectrum management and network security. In this regard, Idris *et al.* [8] reviewed the impact of CRNs and machine learning on spectrum sensing and management within VANETs and on mitigating security issues. This study provides a detailed analysis of how these technologies can optimize spectrum utilization and strengthen threat protection in vehicular networks.

The decision-making process in CRNs has received less attention than other processes despite its importance in spectrum management. In this regard, Ramírez *et al.* [9] examined the decision-making process within Decentralized Cognitive Radio Networks (DCRNs). Using a simulation framework grounded in precise spectrum occupancy data, the study assessed the performance of three multi-criteria decision-making methods. It introduced a user-driven information-sharing strategy to enhance coordination. The results showed a balanced spectrum allocation, demonstrating the relevance of these approaches in CRN management.

Power allocation in cognitive radio networks is another critical challenge. Zhang *et al.* [10] proposed a neural network-based approach to maximize the SU secrecy rate while respecting power and interference constraints. This machine learning-based approach enables more efficient power allocation with lower computational complexity. The results indicate that the proposal can achieve a secrecy rate above 94%, highlighting its effectiveness in practical scenarios.

Based on the studies described, the references analyzed are relevant to contextualize and substantiate the research gap addressed in this work. In particular, the research considered identifies current limitations in the field of study. It highlights the need for new approaches focused on classifying spectral occupancy as a key element in decision-making. Furthermore, the review integrates recent and relevant works, ensuring in-depth and up-to-date coverage of the literature. The contributions, limitations, and gaps identified in the reviewed studies are summarized in Table I, providing a structured view of the motivations driving the development of this research.

TABLE I. COMPARATIVE ANALYSIS LITERATURE REVIEW

Ref.	Topic	Gap	Lationship
[6]	Application of deep learning in CRN to improve efficiency, adaptability, and security in B5G/6G networks.	Lack of specific integration of spectral feature extraction using DL and spectrum classification.	Confirms the value of DL in CRN; reinforces the approach of using deep features for decision-making.
[7]	Comparison of ML techniques for primary user detection in CRN.	Comparison focused on detection techniques, not on DL+ML integration or spectral classification.	Supports the selection of ML classifiers (BDT, DAC, knNC, SVM) in the proposed model.
[8]	Use CR and ML to solve vehicular network spectrum sensing and security problems.	Focus on VANETs, not general CRNs or spectral feature classification with DL.	It supports ML use in critical CRN applications and justifies the need for robust methods such as those proposed.
[9]	Methodological proposal for decision-making in DCRN through information exchange.	Does not use DL-based feature extraction or spectrum classification.	Direct relationship: contributes to the efficient decision-making context that our approach seeks to improve with DL+ML.
[10]	Secure power allocation in CRNs using neural networks for low-latency transmission.	Power optimization, not spectrum classification or multi-user decision-making based on DL+ML.	Evidence of the effectiveness of DL in critical CRN applications, supporting the use of DNNs in our feature extraction approach.

C. Organization of the Document

This paper is organized and presented in four sections including the introduction. The second section describes the methodology, presents the strategy implemented and describes in detail each of the stages of the work. The third section presents the results obtained and the respective quantitative analysis. Finally, the fourth section presents the general conclusions of the work.

II. METHODOLOGY

Fig. 1 presents the diagram of the strategy implemented. The classification of spectral occupancy for decision-making in cognitive wireless networks implementing machine learning is carried out through four stages. The first stage is defined as "Input", it is responsible for converting the power matrix to RGB figures. The second stage is defined as "Feature Extraction", it is responsible for calculating the activations of the deep network learning layers, this is done through the Matlab Deep Learning toolbox. The third stage is defined as "Multiclass and Decision Making", it oversees training and validating the four classifiers that are going to be implemented, additionally, establishing the operation ranking for the decision-making process, transforming the classification of the figures into time and frequency information. The fourth stage, defined as "Output" generates the metrics. Each of the stages is described in detail below.

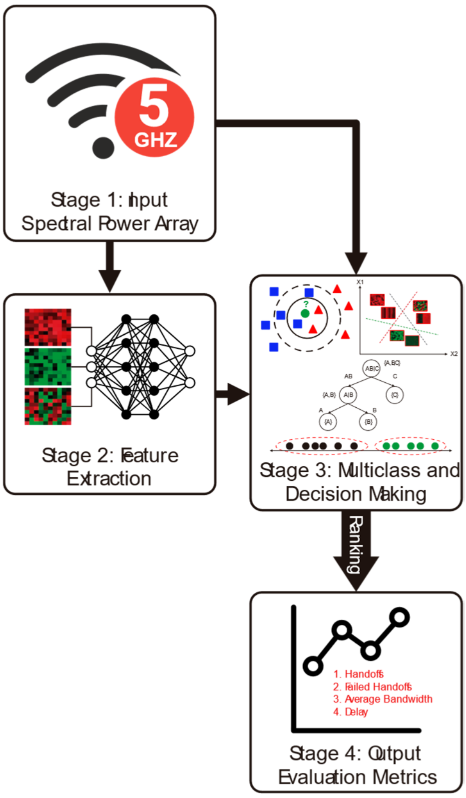

Fig. 1. Structure by stages of the implemented strategy.

A. Stage 1: Input – Spectral Power Array

Spectral occupancy has a relevant role in the decision-making analysis for Cognitive Radio Networks, it allows to characterize the behavior of PUs and according to a set of rules to make access decisions. For this work, the input information corresponds to the spectral power measured experimentally in the Wi-Fi 5GHz bands using the energy detection technique, this technique estimates the signal by comparing the received energy with a known threshold resulting from the noise data [11].

Due to the type of classifiers to be implemented, it is necessary to identify a group of data from the measured data that allows training the models and another group of data that allows them to be validated. The classification of the input information according to the amount of data and the application allowed to define an input database, the size is shown in Table II, where the rows represent the time in seconds and the columns the frequency channels. Both databases have information on 500 frequency channels, for one hour for Training and 10 ms for validation.

TABLE II. DATABASE STRUCTURE FOR THE AVAILABILITY MATRIX

Availability Matrix	Rows	Columns
Training	5,928	500
Validation	988	500

After the construction of the database, the information is converted into figures using an RGB chromatic model. The conversion is carried out by implementing a linearity relationship through a conversion range, where the limits are obtained by identifying the highest and lowest power level. In addition, the limits are taken as the basis for a per-unit adjustment of the other values. Fig. 2 illustrates the power matrix representation using the RGB chromatic model, where green tones indicate low traffic levels and red tones represent high traffic intensity. The origin is a reference point corresponding to a threshold level calibrated for the model's input. In this study, the threshold was set at −79 dBm.

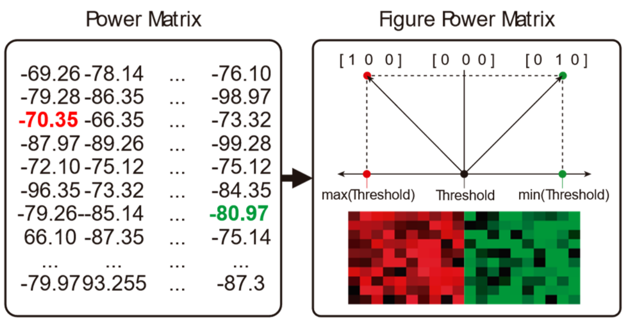

Fig. 2. Representation of the power matrix in RGB chromatic model.

B. Stage 2: Feature Extraction

Feature extraction is the process of converting raw data into a structured set of numerical features that can be used for analysis or modeling. This process can be carried out either manually or automatically. Manual feature extraction involves identifying and defining relevant characteristics based on domain knowledge tailored to the specific problem. In contrast, automatic feature extraction, a method that significantly reduces human effort, leverages specialized algorithms to extract meaningful patterns or attributes directly from signals or images [12]. Deep learning algorithms are widely applied in object extraction, classification, and recognition tasks. Convolutional Neural Networks (CNNs) stand out as a powerful deep learning approach that automatically learns relevant features from data. However, CNNs typically require large datasets to effectively identify and combine features suitable for accurate extraction and classification [13]. The most common approach is to implement pre-trained networks.

In this work, the deep convolutional neural network AlexNet is implemented, which was pre-trained with over a million images. Fig. 3 illustrates the network architecture, composed of eight layers: Five convolutional layers and three fully connected layers. The output of the last layer produces a probability distribution over 1,000 classes [14].

The main objective is to use AlexNet to extract, specifically from the fc7 layer, a representative set of features from the images collected in Stage 1. These features are then used to train and validate four supervised classification techniques.

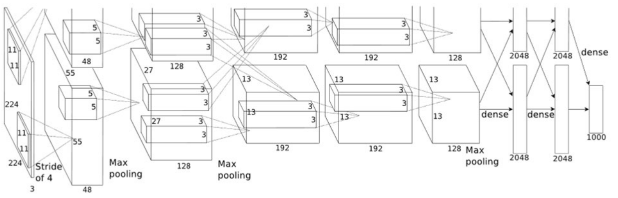

Fig. 3. AlexNet convolutional neural network architecture.

C. Stage 3: Multiclass and Decision Making

A correct decision-making process depends on the estimation of the behavior of the PU; this work characterizes the PU through the classification of the figures that represent the power matrix.

1) Multi-class

As a supervised learning technique, classification is a statistical tool, which through a set of training data allows you to define classification rules to establish class covariates and labels. Classification rules are used for class predication of new objects whose covariates are available [15]. There are various classification strategies, and the challenges grow exponentially, there is no one technique that is the best, each classifier has a considerable number of advantages and disadvantages. This paper implements and analyzes four machine learning classification techniques: BDT, DAC, KNNC, and SVM.

For this work it is required that the classifier be able to identify three types of classes or traffic levels. Many of the classification techniques are originally designed to solve binary problems (two classes). However, for various scenarios, classification problems involve more than two classes. The BDT, DAC, KNNC and SVM techniques can work under multi-class scenarios.

The BDT, DAC, KNNC, and SVM classifiers were selected based on their complementarity in terms of performance with different data types [16].

BDT is a rule-based method that facilitates decision interpretability [17, 18], while DAC is an efficient linear model when the data present well-defined structures [19], [20]. KNNC, on the other hand, is an instance-based classifier that does not assume a specific distribution, making it useful in data sets with complex patterns [21]. Finally, SVM is widely used for its ability to handle high-dimensional data and its robustness against overfitting through kernel functions [22, 23].

This combination of classifiers allows for evaluating the performance of rule-based approaches, statistical models, proximity methods, and optimal margin techniques, providing a comprehensive comparative analysis to select the most appropriate model for the problem at hand.

The objective is that each figure in RGB is classified according to three levels of traffic: high traffic, medium traffic and low traffic, each of these levels and their respective description is presented in Table III. Below is an overview of the four machine learning classification techniques used.

TABLE III. DESCRIPTION OF TRAFFIC LEVELS

Traffic Level	Description
High	This scenario is characterized by limited spectral opportunities due to a high concentration of licensed users
Low	A scenario with abundant spectral opportunities, where the number of licensed users is low or approaching zero.
Middle	A scenario with moderate spectral opportunities, where the number of licensed users is at an intermediate level, allows both SU and PU to coexist and operate within the same spectral environment.

a) Binary decision tree − BDT

This classification technique is based on recursive partitioning, where the dataset is progressively divided into increasingly homogeneous subsets. At each step, the algorithm selects the most informative attribute and an associated threshold to split the data, aiming to maximize the uniformity of class labels within each resulting group. The classification of a sample is achieved by tracing a path from the root node, which plays a crucial role as the starting point, to a leaf node, where a specific class label is assigned (Fig. 4). This splitting process continues at each node until further divisions no longer yield improvements in classification accuracy. One of the key advantages of the decision tree classifier lies in its interpretability: The resulting series of decision rules is straightforward to follow and offers insights into the logic and structure of the modeled system [17, 18].

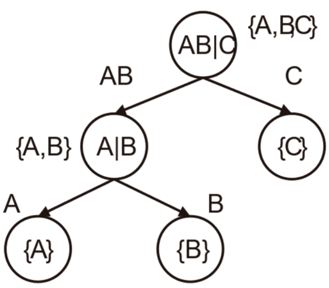

Fig. 4. BDT structure.

b) Discriminant analysis classifier − DAC

Discriminant Analysis is a classification approach where the categories or groups are predefined, and the objective is to assign new observations to one of these known groups. The method seeks to identify a linear combination of input features that maximizes the separation between different classes while minimizing the variation within each class (Fig. 5). In addition to its classification capabilities, discriminant analysis is often applied as a dimensionality reduction technique during data preprocessing, particularly in machine learning and pattern recognition tasks. By projecting high-dimensional data into a lower-dimensional space, it enhances class separability and facilitates the modeling of inter-group differences [19, 20].

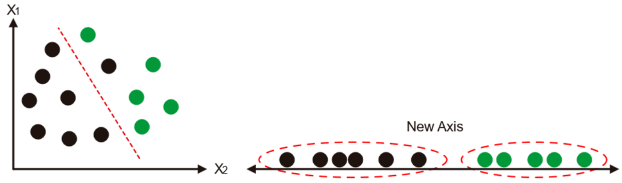

Fig. 5. DAC structure.

c) Nearest neighbors K classifier − KNNC

Classifier, a supervised learning algorithm, is known for its ease of implementation. Its simplicity and efficiency are additional advantages. It operates by identifying the data points in the training set that are closest to a given input. The classification or prediction is then made based on the majority class among the nearest neighbors or, in the case of regression, by averaging their values (Fig. 6).

Fig. 6 represents the classification process. The green dot must be classified by observing its nearest neighbors within a defined radius. Since most of the closest neighbors are red triangles, the green dot would be classified in that category.

KNNC can be applied to both classification tasks involving discrete labels and regression problems involving continuous outputs. Its core principle relies on comparing the input sample to previously seen instances and assigning a label based on the most similar—or nearest—examples encountered during training [21].

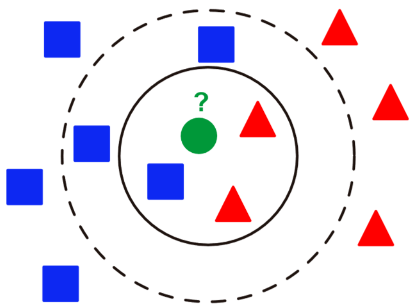

Fig. 6. KNNC structure.

d) Vector support machines – SVM

Based on the principle of identifying the optimal hyperplane that maximally separates two classes in a binary classification task (Fig. 7) [24].

Fig. 7 represents a classifier that separates three classes using hyperplanes. Each dashed line shows possible decision boundaries. The SVM algorithm constructs multiple hyperplanes to maximize the margin between each pair of classes, thus achieving the best possible separation in the feature space.

The algorithm aims to maximize the margin—the distance between the hyperplane and the nearest data points from each class—to improve generalization performance. In its standard form, SVM is inherently designed for binary classification and does not natively handle multi-class problems. However, multi-class classification can be achieved by decomposing the original task into multiple binary classification subproblems and applying the same margin-maximizing strategy in each case [22, 23].

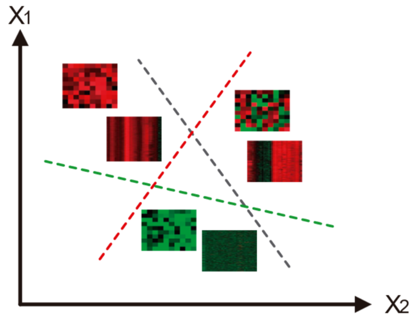

Fig. 7. SVM structure.

e) Decision-making

Once the classifier identifies the figures corresponding to high, medium, and low traffic levels, a spectrum access decision must be made. To guide this process, a "Ranking" vector is constructed by assigning scores to each traffic zone to identify channels offering the highest number of spectral opportunities. Channels with the highest scores associated with low traffic occupy the top positions in the Ranking vector and are prioritized for SU data transmission. If a selected channel is found to be occupied, the system proceeds to the next best-rated option. The Ranking vector uses temporal and frequency information from figures with low and medium traffic. Data from high-traffic classifications are excluded, as such zones represent areas with limited spectral availability and are, therefore, unsuitable for efficient spectrum use.

D. Stage 4: Output − Evaluation Metrics

To evaluate the decision-making process through the four machine learning classification techniques, four performance metrics are established. Table IV provides each metric's name, description, and classification type. The classification indicates whether the metric is a benefit type (where higher values are preferable) or a cost type (where lower values are more desirable).

TABLE IV. PERFORMANCE METRICS

Name	Description	Guy
Cumulative average handoff number	It is the total number of handoffs performed	Cost
Cumulative average number of failed handoffs	It is the handoff number that the SU could not materialize because it found the respective spectral opportunities occupied	Cost
Average bandwidth	This is the average bandwidth used by the SU	Benefit
Cumulative average delay	It is the total average time experienced by the SU	Cost

E. Model Training and Validation Characteristics

The model training and validation process was carried out using cross-validation, a technique widely used in machine and deep learning classification problems.

A total of 500 traffic figures were used for the training and validation of each classifier, of which 70% were used for training (350 figures) and 30% for validation (150 figures). It is important to clarify that the 500 figures were used only for cross-validation of the classifiers.

Prior to this process, the input database was analyzed statistically to analyze the information and filter outliers, thus ensuring the quality of the data used in training.

Regarding the classification techniques, the classifiers were selected based on their complementarity in terms of performance across different data types. This combination allowed for evaluating the performance of rule-based approaches, statistical models, proximity methods, and optimal margin techniques, thus providing a comprehensive comparative analysis.

It is worth noting that the classifiers were implemented using the functions available in the Matlab-R2021b toolbox, which allowed for efficient integration of the techniques without the need to program them from scratch. This choice guarantees the robustness and efficiency of the applied methodology by leveraging optimized and validated tools within the Matlab-R2021b environment.

III. Results

This section presents and discusses the results obtained from simulations. The experiments used MathWorks Matlab-R2021b as the simulation environment, running on a 64-bit Microsoft Windows 10 operating system.

A. *Simulation Parameters*

Table V presents the simulation parameters and respective settings used to evaluate spectral traffic classifiers in CRN using deep learning and machine learning techniques.

TABLE V. Simulation Parameters and Settings

Parameter	Setting
Simulation time	9 minutes
Deep Network	AlexNet
Multiclass classification strategy	*Binary Decision Tree (BDT) *Discriminant Analysis Classifier (DAC) *K-Nearest Neighbors (KNNC) *Support Vector Machines (SVM)
Type Traffic	Wi-Fi 5GHz
Threshold	−79 dBm

In this research, two comparative analyses are performed. The first analyzes the training and validation process of each of the classification techniques, using the confusion matrix as an evaluation tool. To ensure a fair comparison, all classifiers are evaluated under the same scenario, corresponding to the same information in the spectral power matrix.

The second analysis focuses on spectral mobility, evaluated by classifying traffic levels. This analysis allows the calculation of the evaluation metrics for each classifier: Cumulative Average Handoff Number, Cumulative Average Number of Failed Handoffs, Average Bandwidth, and Cumulative Average Delay.

Spectral mobility is associated with the channel changes that an SU must perform. A search algorithm is implemented for its analysis, which is described in detail in Ref. [25]. This algorithm performs column hops in the spectral matrix until it finds an available channel in the availability matrix. Column and row hops, search time, and availability are stored to quantify the spectral handoff and failed handoff metrics.

An assertive decision-making process directly impacts the Bandwidth and Delay metrics, as the total number of handoffs performed influences both and failed during the transmission time. The methodology and mathematical model used to calculate these metrics are described in detail in Ref. [25]. This research generates the availability matrix from a threshold criterion defined in Refs. [26, 27]. According to the data used, the transmission time corresponds to nine minutes (9 m).

The authors developed the simulation tool, which is registered with the National Copyright Office of the Colombian Ministry of the Interior. The Universidad Distrital Francisco José de Caldas holds the property rights to this work. The publication associated with the simulator is presented in Ref. [28].

B. *Algorithm Performance*

The confusion matrix was used as a performance metric. Figs. 8−11 show the confusion matrix obtained for the BDT, DAC, KNNC and SVM classifiers. From the analysis of the results, it is identified that the best prediction is for the high and medium traffic levels, with a correct classification of 100% for the two traffics with the four techniques, except for BDT in high traffic, where a correct classification of 90% is presented. For all four techniques, low traffic has a correct ranking of 68% for KNNC and SVM and 76% for BDT and DAC.

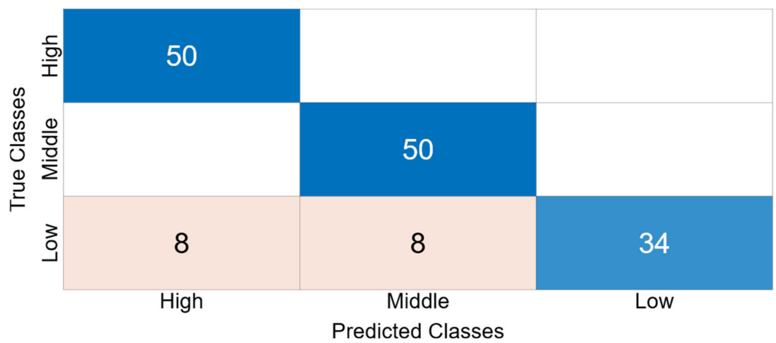

Fig. 8. Confusion matrix for BDT.

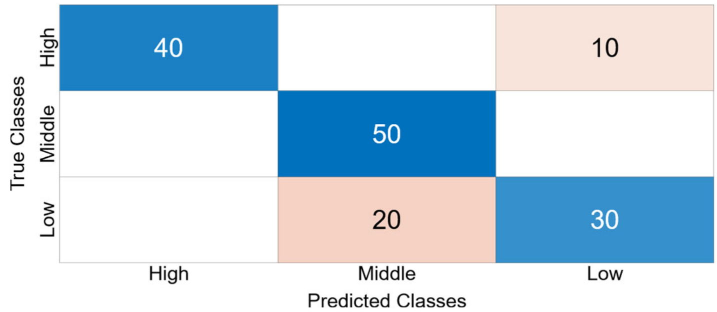

Fig. 9. Confusion matrix for DAC.

Fig. 10. Confusion matrix for KNNC.

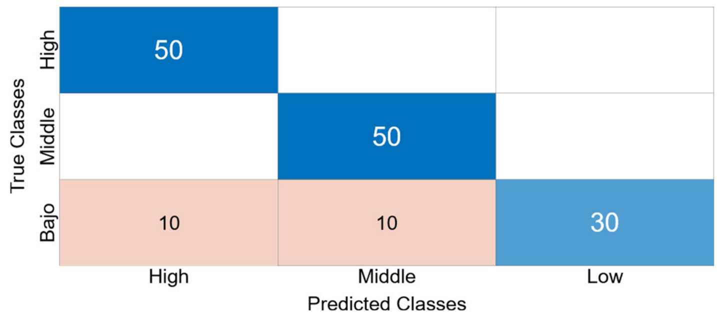

Fig. 11. Confusion matrix for SVM.

C. *Evaluation Metrics Decision Making Process*

As results, the four-performance metrics obtained for the decision model using feature extraction are presented. Figs. 12−14 presents respectively, for the four classifiers, the number of cumulative average handoffs, the number of cumulative average failed handoffs, and the average bandwidth during a 9 m transmission.

Figs. 12−13, being cost metrics, show that the SVM classifier presents the best performance with the lowest number of cumulative average handoffs and cumulative average failed handoffs. The second-best classifier is BDT followed by KNNC, finally the lowest performance is obtained by DAC.

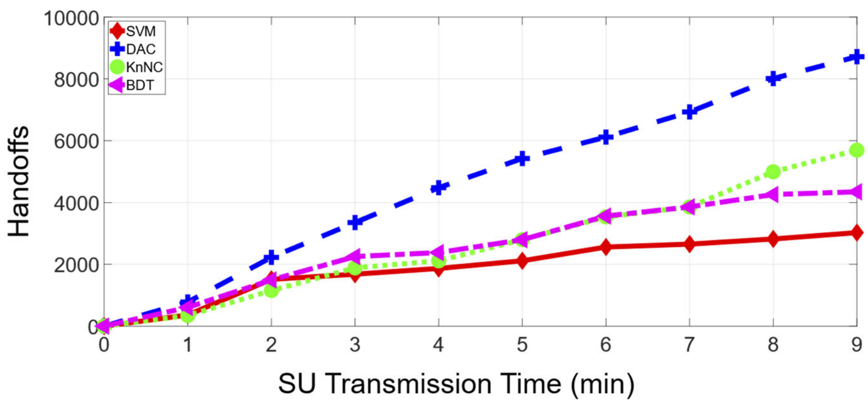

Fig. 12. Cumulative number of total handoffs.

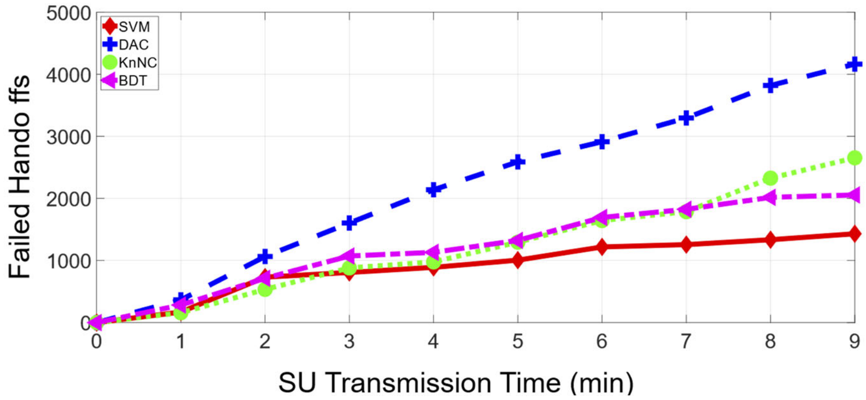

Fig. 13. Cumulative number of failed handoffs.

Fig. 14, as benefit metrics, shows that the KNNC and DAC classifiers present the worst performance with the highest average bandwidth during the 9 ms of transmission. The SVM during the range of 0 m–6 m presents the best performance with the highest average bandwidth, for the remaining time range BDT obtained the best performance.

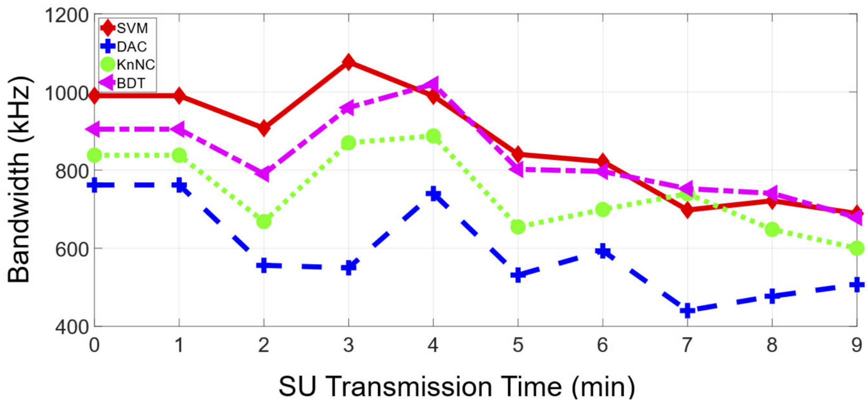

Fig. 14. Average bandwidth.

Fig. 15 shows the average delay during a transmission of 9000 kB for the four classifiers. As it is a cumulative cost metric, it is observed that the SVM classifier presents the best performance with the lowest total average time experienced by the SU, the second-best classifier is BDT followed by KNNC, finally the lowest performance is obtained by DAC.

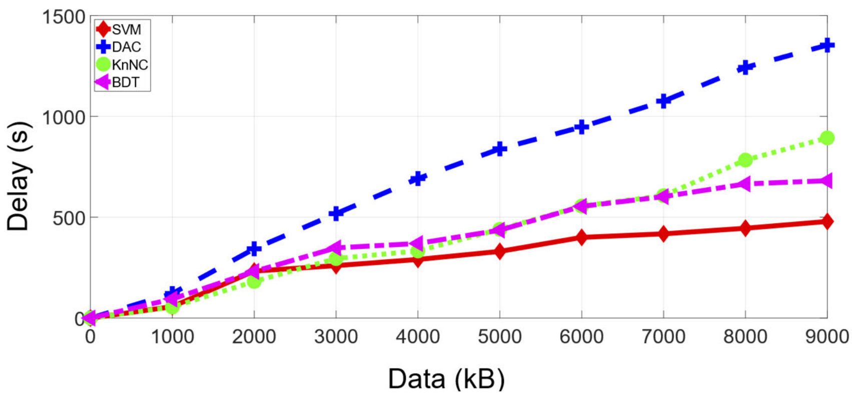

Fig. 15. Average delay.

D. Analysis of Results and Discussion

According to the results obtained, the respective analysis of results and their respective discussion are presented below.

1) Analysis of results

Table VI summarizes the cumulative metrics recorded over 9 ms. The values for the number of failed handoffs and total handoffs represent the overall counts during this interval. In the case of delay, the reported value corresponds to the average total transmission time experienced by the Secondary User (SU) while transmitting 9,000 kB of data.

TABLE VI. TOTAL COST METRICS FOR CLASSIFIERS

Sorter	Total handoffs	Failed handoffs	Average Delay
BDT	4345	2056	681.08
DAC	8718	4164	1353.20
KNNC	5693	2654	893.18
SVM	3025	1431	479.07

According to the results obtained in Table VI, Fig. 16 is generated. The figure shows that the SVM classifier showed the best overall performance across all three-cost metrics. With 3,025 handoffs, SVM maintains the lowest number among the classifiers, suggesting an efficient and conservative strategy for managing connection changes. In comparison, BDT increases the number of handoffs by 1.44 times, KNNC by 1.88 t, and DAC reaches the highest value, with a 2.88-fold increase compared to SVM.

This same pattern is evident in failed handoffs, where SVM again has the fewest (1,431), while BDT, KNNC, and DAC show increases of 1.44 s, 1.85 s, and 2.91 s, respectively. These results indicate that SVM reduces the number of handoffs and improves their effectiveness by minimizing the number of failed handoffs.

Regarding average delay, SVM is positioned as the most efficient classifier with a value of 479.07 ms. In contrast, BDT shows a 1.42-fold increase, KNNC a 1.86-fold increase, and DAC achieves the highest value with a 2.82-fold increase compared to SVM. This advantage in terms of latency reinforces SVM's superiority in making fast and effective decisions during the handoff process, which is critical for maintaining quality of service in mobile networks.

Overall, the results position SVM as the most efficient classifier for the scenarios proposed in this research.

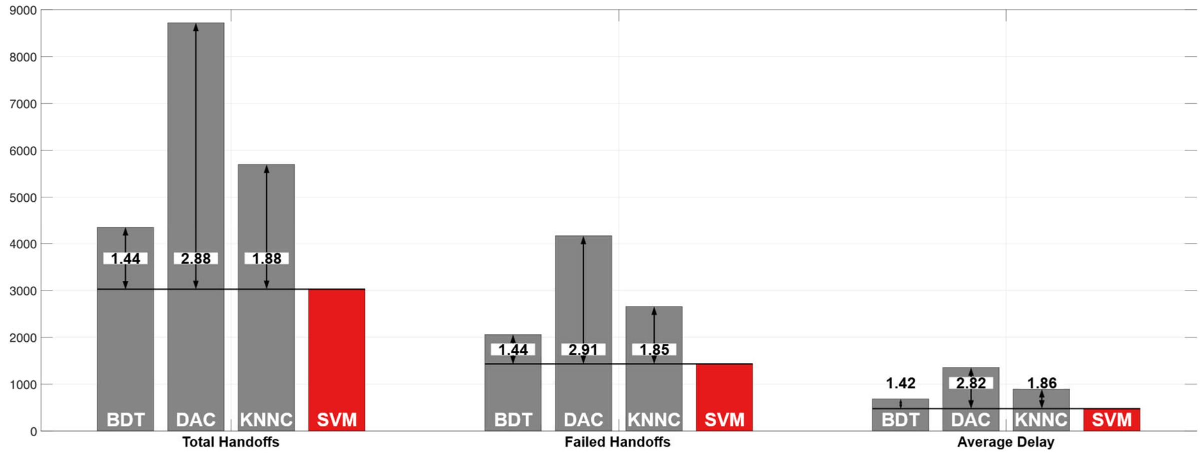

Fig. 16. Comparison of the performance of the classifiers in terms of cost metrics.

2) *Discussion*

The results show that the SVM classifier significantly improved the efficiency of the CRN by reducing both the total number of handoffs and the number of failed handoffs. This reduction in the metrics associated with operating costs suggests that the decision-making process was improved, thus promoting more stable communication for the SUs by reducing channel changes and the interference generated.

Regarding the key quality of service indicators, Bandwidth and Delay reflect the CRN's reliability level. An increased available bandwidth was observed, indicating that the SUs could more efficiently exploit spectral opportunities, maximizing adequate transfer capacity without affecting primary users. On the other hand, Delay, associated with the spectral handoff process, tends to impact system performance when it increases negatively. In this context, the decrease recorded in this metric represents a substantial improvement in the overall network performance.

E. *Real-World Applications*

CRNs improve the use of the radio spectrum, driving economic and social development. They facilitate access to broadband internet in underserved communities, enable e-health solutions in the healthcare sector, and deploy smart sensors for autonomous monitoring in production environments.

IV. CONCLUSION

CR provides various solutions through dynamic spectrum utilization, making it a technology of significant interest in academic and industrial domains. This study focuses on spectral occupancy classification to support decision-making, employing feature extraction techniques in combination with machine learning algorithms. Feature extraction is performed through the activation layers of a convolutional neural network previously trained. With the characteristics obtained, four machine learning classifiers (BDT, DAC, KNNC, and SVM) are trained, the objective of the classification is to identify traffic levels that allow estimating the characterization of the PU to carry out a correct decision-making process. To evaluate the intake process, three cost metrics and one benefit metric were used, for the metrics the analysis of results showed that the SVM classifier presents the best performance, followed by KNNC and DAC, the lowest performance with the poorest performance indicators is obtained by BDT.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

C. Hernández conceptualized and conducted the research; D. Giral-Ramírez and C. Hernández developed the methodology; D. Giral-Ramírez developed the software; E. Cadena analyzed the data; D. Giral-Ramírez and E. Cadena validated the results; C. Hernández and E. Cadena performed the formal analysis; D. Giral-Ramírez, C. Hernández and E. Cadena wrote, reviewed, and edited the manuscript; all authors had approved the final version.

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