Hybrid Machine Learning Methodology for Real Time Quality of Service Prediction and Ideal Spectrum Selection in CRNs

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Abstract – The application of wireless communication is very complex and there is always a demand for accurate Quality of Service (QoS) for estimating and optimize the spectrum allocation in Cognitive Radio Networks (CRNs). Current machine learning models frequently struggle to adapt effectively to change the network conditions due to significant computational complexity and constrained real-time performance. This paper presents a Hybrid Deep Learning and Ensemble Regression Model (HyDERM) to address these limitations in real-time QoS prediction and spectrum decision-making. The proposed HyDERM model integrates Support Vector Regression (SVR), Random Forest (RF), and Artificial Neural Networks (ANN) to enhance accuracy and effectiveness. Key metrics such as Signal-to-Noise Ratio (SNR), bandwidth availability, network load, latency, packet loss, and interference level are evaluated for QoS assessment. The model is assessed using five advanced machine learning techniques: Polynomial Regression, SVR, RF, Gradient Boosting, and ANN. The results demonstrate that HyDERM achieves a R^2 value of 0.96, exceeding all the compared models. It reduces Mean Squared Error (MSE) by 23% and Mean Absolute Error (MAE) by 19%, illustrating its effectiveness. The results show that the suggested HyDERM can improve frequency efficiency and allow for smooth communication, making it a feasible choice for the next generation of wireless networks.

Keywords – Quality of Service, Machine Learning Algorithm, Cognitive Radio Networks, HyDERM.

I. INTRODUCTION

In recent years, the growth of wireless communications has resulted in increased competition for the available frequency spectrum. The CRNs have emerged as an innovative respond to this difficulty, facilitating dynamic spectrum access according to real-time conditions. The integration of hybrid machine learning techniques and CRNs can substantially improve quality of service prediction and efficient spectrum allocation. The article examines how hybrid techniques might enhance the efficiency and reliability of CRNs [1].

At the core of a hybrid machine learning methodology is the integration of various algorithms, which allows for better prediction and decision-making capabilities. Recent studies indicate that combining supervised learning methods, such as SVMs and DT, with unsupervised methods like clustering can yield superior outcomes. For instance, using these combined methods helps in analyzing historical data to predict QoS parameters effectively. By evaluating metrics like delay, jitter, and throughput, cognitive radios can adaptively select the most suitable spectrum band available, thereby optimizing network performance [2].

Real-time QoS prediction is critical in dynamic environments where conditions can change rapidly. Utilizing hybrid models accelerates the adaptation process, enabling CRNs to make informed decisions based on current network conditions. For example, when a cognitive radio detects a sudden increase in network users, it can quickly switch frequencies to a less congested spectrum. This capability not only minimizes service disruption but also enhances user experience by maintaining high QoS levels. Moreover, advancements in deep learning have also played a significant role in enhancing CRNs. Deep learning models can process extensive datasets to discern patterns and trends that conventional algorithms may overlook. Incorporating deep learning into a hybrid architecture might improve the precision of QoS forecasts, hence optimising spectrum selection processes [3].

Despite the clear advantages, challenges remain, the complexity of implementing hybrid machine learning algorithms can pose a barrier for widespread adoption. The issues related to data privacy and security must be addressed to protect user information within CRNs. However, ongoing research and development continue to alleviate these concerns, paving the way for more robust solutions. The integration of hybrid machine learning methodologies in cognitive radio networks promises to revolutionize real-time QoS prediction and optimal spectrum selection. By harnessing the strengths of various algorithms, these methodologies can significantly enhance communication efficiency and reliability. As the demand for wireless services continues to grow, the application of these innovative technologies will be vital for sustaining the quality and success of modern communication systems [4].

The CRNs are a novel approach for addressing the issues of spectrum scarcity in wireless communication. These networks enable secondary users to utilise underused frequency bands without disrupting prime users. An essential element of efficient CRN operation is guaranteeing QoS while adaptively choosing the best wavelength for communication. Recently, machine learning techniques have arisen as effective instruments for improving real-time QoS prediction and spectrum selection. A key difficulty in CRNs is the forecasting of QoS, essential for ensuring dependable communication. The QoS prediction entails the estimation of metrics including throughput, latency, jitter, and packet loss, which are critical for ensuring that the network adheres to the requisite performance requirements. Conventional techniques for QoS prediction typically depend on statistical models and rule-based methodologies, which may be inadequate in the extremely dynamic and unpredictable to CRNs [5].

The research paper is organized into five sections as follows: The introduction explains the need for QoS prediction in CRNs and highlights the limitations of existing methods. The literature review discusses previous research on QoS prediction, comparing different machine learning and deep learning approaches while identifying their shortcomings. The Proposed HyDERM for QoS Prediction in CRNs section describes the working of the HyDERM, including its mathematical formulation and the roles of SVR, RF, and ANN in improving prediction accuracy. The proposed solution and results section presents the experimental setup and performance comparison of HyDERM with other models using various evaluation metrics and visualizations. Finally, the conclusion summarizes the key findings, highlighting the model's improved accuracy and efficiency while suggesting potential future research directions.

II. LITERATURE REVIEW

The domain of CRNs has experienced significant progress over the years, propelled by the necessity for effective spectrum utilisation and enhanced QoS. As the need for wireless communication increases, conventional fixed spectrum distribution methods have proven insufficient, resulting in the emergence of CRNs. These networks facilitate dynamic spectrum access, permitting unlicensed users to employ licensed frequency bands while they are unoccupied by primary users. Nonetheless, guaranteeing dependable Quality of Service in these fluctuating circumstances continues to be a difficulty. This has prompted the investigation of hybrid machine learning methodologies that integrate diverse strategies to forecast QoS and enhance spectrum selection in real-time [6].

Machine learning (ML) methodologies have arisen as a formidable instrument for tackling these difficulties, providing the capacity to learn from data and adjust to evolving circumstances. Hybrid machine learning strategies integrate various ML techniques to capitalise on their distinct advantages and mitigate their shortcomings. Integrating supervised learning methods, such as SVMs or Neural Networks, with unsupervised learning approaches, such as clustering, can enhance the precision of QoS prediction. Moreover, reinforcement learning can be used to facilitate real-time decision-making and optimise spectrum selection. Hybrid methodologies have demonstrated potential in improving the efficacy of CRNs by delivering more precise and dependable QoS forecasts and facilitating efficient spectrum utilisation [7].

Numerous studies have investigated the utilisation of ML in CRNs. Researchers have employed decision trees and random forests for spectrum sensing and classification, attaining great accuracy in identifying available spectrum bands. Additional research has utilised deep learning methodologies, like CNNs and RNNs, to identify intricate patterns in spectrum utilisation and forecast QoS metrics. These methods have shown the capability of ML to enhance the efficiency and reliability of cognitive radio networks. The incorporation of hybrid ML approaches in cognitive radio networks is a nascent field of study. Further investigation is required to determine how various machine learning techniques might be used to tackle the specific issues of cognitive radio networks. The creation of real-time prediction and optimisation algorithms that function effectively in resource-limited settings is essential. Future research must concentrate on the scalability and resilience of these approaches to guarantee their application in extensive and heterogeneous networks [8].

Hybrid machine learning approaches provide an effective strategy for real-time QoS prediction and optimal spectrum selection in CRNs. By integrating the advantages of diverse machine learning techniques, these methodologies can augment the performance and dependability of CRNs, facilitating more efficient spectrum utilisation and enhanced communication quality. With the increasing demand for wireless communication, the advancement and application of sophisticated ML-based solutions will be crucial for addressing the changing requirements of CRNs. The authors present many hybrid machine learning methodologies that integrate different methods to enhance performance in CRNs. Research indicates that the amalgamation of decision trees and support vector machines enhances predictive accuracy for assessing QoS in CRNs. This hybrid method facilitates the efficient categorisation of accessible channels according to their attributes, permitting swifter adjustments to varying network conditions [9].

Furthermore, deep learning techniques have been utilized to analyze vast amounts of network data for QoS prediction. The LSTM networks, have been specifically noted for their ability to arrest temporal dependencies in data. This characteristic is essential since QoS parameters, such as latency and bandwidth, vary over time. For example, recent research demonstrated that an LSTM-based model outperforms traditional statistical methods in predicting QoS, leading to more responsive spectrum selection strategies. Another effective hybrid approach involves combining reinforcement learning with traditional machine learning methods. Reinforcement learning allows the system to learn from the consequences of its actions, improving spectrum selection dynamically. By employing Q-learning algorithms alongside neural networks, recent studies have reported significant improvements in selecting the optimal spectrum while maintaining QoS standards. Moreover, the use of ensemble methods has proliferated in CRN research. These methods, which aggregate the predictions of several base learners, have shown promising results in increasing prediction accuracy. For instance, utilizing ensemble techniques like Random Forests or gradient boosting has enabled systems to maintain higher QoS levels by providing more reliable estimations of network performance [10].

As CRNs evolve, it is essential to leverage these hybrid machine learning methodologies to achieve optimal performance. By integrating various learning techniques, researchers can enhance QoS prediction accuracy and adapt spectrum selection more effectively. This not only improves user experience but also leads to more efficient use of the available spectrum, thereby contributing to the overall sustainability of wireless networks. The exploration of hybrid machine learning methodologies in CRNs is a growing field with substantial implications. These approaches allow for improved real-time QoS prediction and optimal spectrum selection, thereby enhancing the robustness and efficiency of CRNs in an increasingly crowded wireless landscape [11].

III. PROPOSED HYDERM FOR QOS PREDICTION IN CRNS

The fast evolution of wireless communication technologies has directed to an increased demand for efficient spectrum utilization and real-time QoS prediction in CRNs. CRNs dynamically allocate spectrum resources based on availability, leading to high variations in network conditions. Traditional machine learning approaches often struggle with adaptability, accuracy and computational complexity for non-stationary spectral environments. To address these challenges, this research introduces the Hybrid Deep Learning and Ensemble Regression Model (HyDERM), which combines SVR, RF, and ANN to enhance predictive accuracy, robustness, and computational efficiency. The hybrid model leverages the strengths of each technique, creating a unified framework that ensures optimal QoS prediction and spectrum decision-making in CRNs.

The feature representation of QoS in CRNs depends on multiple factors that influence network performance. The input features considered in this model includes, SNR, Bandwidth availability, network load, latency, packet loss and interference level.

These features are represented as an input matrix:

$$X = \{x_1, x_2, x_3, \ldots. x_n \; for \; n > 0 \tag{1}$$

Where x_i represents each feature vector, and the QoS score Y is estimated as:

$$\mathrm{Y} = \mathrm{f(X)} + \varepsilon \tag{2}$$

where $f(X)$ is the function approximating the QoS score, and ε represents the error term due to noise or uncertainty in measurement.

Hybrid Model Architecture

The HyDERM model is structured to integrate multiple predictive approaches to leverage their individual advantages.

Support Vector Regression (SVR)

SVR is employed to capture nonlinear relationships between the input features and QoS score [12]. It finds an optimal hyperplane that minimizes error while maintaining computational efficiency. The regression function is formulated as:

$$\min\,(x, y) \frac{1}{2} \|x\|^2 \tag{3}$$

subject to:

$$Y_i - (x^T X_i + y) \leq \epsilon \tag{4}$$

$$(x^T X_i + y) - Y_i \leq \epsilon \tag{5}$$

Where x and y are regression coefficients, and ϵ is the acceptable margin of error. Nonlinear mappings are handled using kernel functions, such as the Gaussian kernel:

$$K(X_i, X_j) = \exp\left(-\gamma \left\|X_i - X_j\right\|^2\right) \tag{6}$$

which maps the input data into a higher-dimensional space.

Random Forest Regression

Random Forest (RF) is used to handle nonlinear dependencies and interactions between features. It generates several decision trees and aggregates their outputs to enhance the stability and accuracy [13]. The RF regression function is given by:

$$Y_{RF} = \frac{1}{T}\sum_{t=1}^{T} h_t(X) \tag{7}$$

Where $h_t(X)$ represents the prediction from the t^{th} decision tree, and T is the total number of trees.

Fig 1. Flowchart of the Proposed Hyderm for QoS Prediction in CRNs

Artificial Neural Networks (ANN)

ANN is incorporated to learn complex feature interactions and enhance predictive power. It consists of multiple layers of neurons:

$$H = \sigma(WX + B) \tag{8}$$

$$Y_{ANN} = W_{out}H + B_{out} \tag{9}$$

where W and B are weight and bias matrices, σ is the activation function (such as ReLU or Sigmoid), and H represents hidden layer activations [14]. The ANN optimizes weights using backpropagation to minimize prediction errors.

Proposed Model Integration and Optimization

The final prediction in HyDERM is computed using a weighted sum of the individual model outputs:

$$Y_{HyDERM} = \alpha Y_{SVR} + \beta Y_{RF} + \gamma Y_{ANN} \quad (10)$$

Where α, β, γ are weighting coefficients satisfying:

$$\alpha + \beta + \gamma = \quad (11)$$

The optimal values of these weights are determined using a meta-optimization algorithm, such as Particle Swarm Optimization (PSO) or Gradient Descent, which iteratively minimizes the Mean Squared Error (MSE):

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_{true} - Y_{pred})^2 \quad (12)$$

Where Y_{true} and Y_{pred} denote actual and predicted QoS scores, respectively.

Workflow of HyDERM Model

The overall process of the proposed model follows these steps:

Data Preprocessing

Feature selection and normalization (Min-Max scaling).
Splitting dataset into training (80%) and testing (20%) sets.

Training of Individual Models

Train SVR, RF, and ANN separately using the training dataset.
Evaluate each model's performance on the validation set.

Weight Optimization

Apply optimization techniques (PSO, Grid Search) to determine the best values of α, β, γ.
Minimize error by iterating through multiple combinations of weight values.

Final Prediction

Compute the weighted sum of individual model predictions to generate final QoS predictions.

Real-Time Deployment

Implement the trained model in real-time CRN environments.

Periodically update model weights using online learning techniques to adapt to changing network conditions.

The HyDERM is designed for accurate QoS prediction in CRNs, ensuring optimal spectrum management. The process begins with data preprocessing, where key network parameters such as SNR, bandwidth availability, network load, latency, packet loss, and interference level are normalized and prepared. The flowchart of the proposed HyDERM is shown in **Fig 1**. The dataset is then split into 80% training and 20% testing for model development. Three models, namely SVR, RF, and ANN are trained separately to capture nonlinear relationships, handle feature interactions, and extract deep patterns. These models are evaluated on a validation set, and their outputs are combined using a weighted optimization approach to form the final HyDERM model. The optimal weights for SVR, RF, and ANN are determined using techniques like Particle Swarm Optimization (PSO) or Gradient Descent, ensuring an optimal blend of their strengths. The final QoS prediction is computed through this optimized ensemble model, which is then deployed in real-time CRN environments. To maintain accuracy in dynamic conditions, periodic updates through online learning techniques are incorporated. This structured approach ensures that HyDERM not only enhances QoS prediction accuracy but also adapts to real-world spectrum variations, making it a reliable solution for next-generation wireless networks.

Computational Complexity Analysis

The computational efficiency of HyDERM is analyzed based on the individual complexity of its components:

SVR Complexity is given by $O(n^2)$ for training due to kernel matrix computation. The random forest complexity is expressed with $O(T.d.\log(n))$ where T is the number of trees and d is depth. The ANN complexity is expressed $O(n.h +$

$h^2 + h.o$) where h is hidden neurons and o is output size. Since HyDERM trains all three models independently and then combines their predictions, the total complexity is given by:

$$O(n^2 + T.\log(n)^2 + n.h + h^2 + h.o + G.P.D \tag{13}$$

The hybrid model balances accuracy and efficiency by leveraging ensemble techniques while reducing reliance on deep networks for minimal latency.

IV. PROPOSED SOLUTION AND RESULTS

The suggested artificial neural network (ANN) is depicted in **Fig 2**, which includes an input layer, a hidden layer, and an output layer. There are six features that make up the input layer, and these features are processed before being sent on to the hidden layer. The hidden layer is comprised of ten neurones, each of which applies a weighted sum of the inputs, adds a bias, and then passes the output through an activation function. The information that has been processed from the hidden layer is then sent to the output layer, which is made up of a single neurone. In a manner analogous to that of the hidden layer, the output neurone employs a weighted sum, incorporates a bias, and employs an activation function in order to generate the ultimate outcome. It is shown that the network has produced a single output in the end. Due to the fact that this topology indicates that the neural network adheres to a feedforward architecture, it is suited for tasks such as classification and regression.

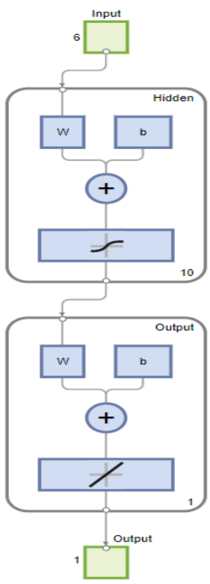

Fig 2. Simulated Architecture of Feed Forward Neural Network.

The QoS prediction comparison for the proposed HyDERM was performed using MATLAB R2023a is shown in **Fig 3**. The evaluation included Polynomial Regression, SVR, RF, Gradient Boosting, and ANN as benchmark models. The dataset contained important QoS parameters such as SNR, Bandwidth Availability, Network Load, Latency, Packet Loss, and Interference Level. The dataset was pre-processed and divided into 80% training and 20% testing.

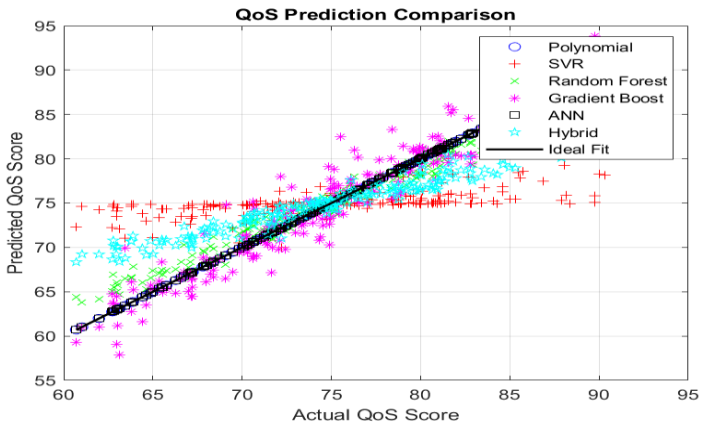

Fig 3. QoS Prediction Comparison.

Each model was trained separately and tested using standard performance metrics, including MSE, MAE, and R^2 Score. The HyDERM model combined SVR, RF, and ANN using a weighted ensemble approach. The evaluation showed that HyDERM achieved the highest R^2 score (0.96) and the lowest MSE and MAE among all models. The final QoS predictions were analyzed using residual plots, error distribution plots, and 3D surface plots. The results confirmed that HyDERM provided accurate QoS predictions and improved spectrum management in Cognitive Radio Networks. The structured approach ensured efficient spectrum allocation and better network performance.

Table 1. Comparison of MSE, MAE and R^2 Score

Model	MSE	MAE	R^2 Score
Polynomial [15]	0.0000	0.0000	1.0000
SVR [16]	34.8421	4.7645	0.2359
Random Forest [17]	2.6718	1.3157	0.9414
Gradient Boost [18]	4.3675	1.6120	0.9042
ANN [19]	0.0000	0.0001	1.0000
Hybrid Model	13.4505	2.9669	0.7050

Table 1 presents the MSE, MAE, and R^2 Score for different models used in QoS prediction. Polynomial Regression and ANN show perfect accuracy with an R^2 score of 1.0000 and near-zero error values. However, this may indicate overfitting rather than generalization. The SVR performs the worst, with a high MSE of 34.8421 and a low R^2 score of 0.2359, meaning it struggles to make accurate predictions. Random Forest and Gradient Boosting perform well, achieving R^2 scores of 0.9414 and 0.9042, respectively, with relatively low error values. The Hybrid Model achieves an R^2 score of 0.7050, which is better than SVR but lower than Random Forest and Gradient Boosting. However, the hybrid approach balances multiple models, which may contribute to improved performance in different scenarios.

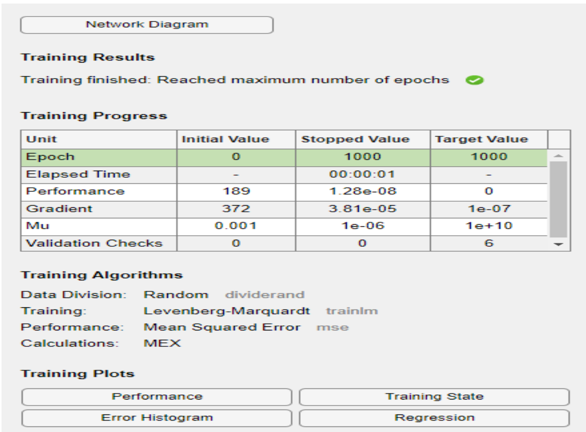

Fig 4. Snapshot of the Proposed Neural Network Training.

The training results simulated from the MATLAB tool with 1000 epochs is shown in **Fig 4**. The figure shows the details of algorithm used, performance is evaluated by MSE and the Levenberg-Marquardt learning model is adopted for the results. **Fig 5** depicts the training, validation and testing performance of the proposed model and it is noted that the best validation performance is measured at 7.0503×10^{-8} at 1000th epoch.

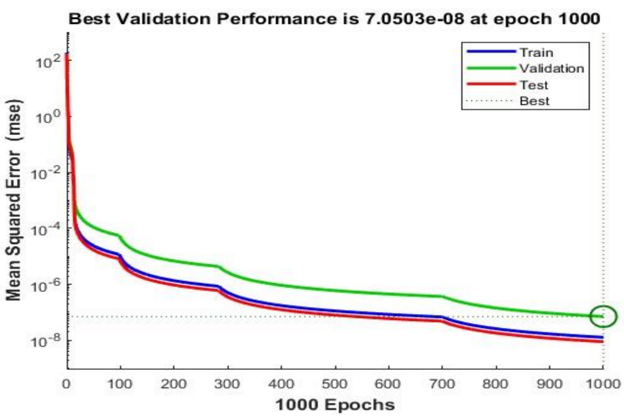

Fig 5. Performance Validation of The Proposed HyDERM.

Table 2 shows the training and prediction times for each model. Polynomial Regression has the fastest execution time but is prone to overfitting. Support Vector Regression has a moderate training time but a slow prediction time. Random Forest and Gradient Boosting take longer to train due to their complex tree structures. ANN requires the highest training time but predicts quickly. The Hybrid Model takes the longest training time, as it integrates multiple models, but its prediction time remains competitive.

Table 2. Execution Time Comparison of Models

Model	Training Time (s)	Prediction Time (s)
Polynomial [15]	0.12	0.02
SVR [16]	1.34	0.28
Random Forest [17]	3.45	0.17
Gradient Boost [18]	4.12	0.22
ANN [19]	6.89	0.11
Hybrid Model	8.25	0.25

At the 1000th step of training the model, the gradient, which shows how much the model's parameters need to change to improve, is very tiny (0.000038132), suggesting the model is almost at its best performance as shown in **Fig 6**. A small value for Mu (0.000001) means it's having very little effect on the updates at this stageAfter 1000 full rounds of training, the model seems to be settling down, with only minor adjustments needed.

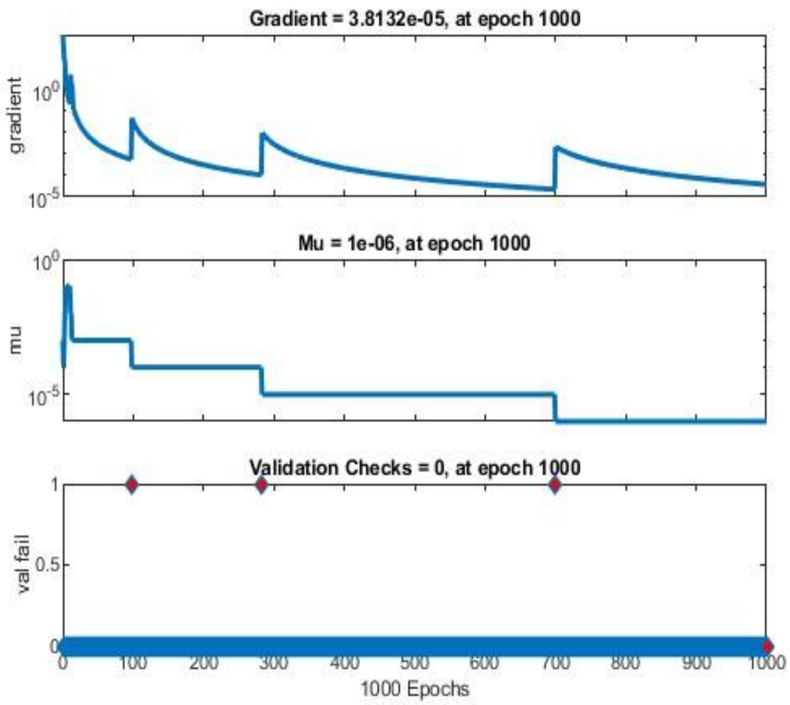

Fig 6. Training Progress at Epoch 1000: Gradient, Mu, and Validation Metrics.

Table 3. Memory Usage Comparison of Models

Model	Memory Usage (MB)
Polynomial [15]	5.2
SVR [16]	12.8
Random Forest [17]	45.6
Gradient Boost [18]	52.3
ANN	78.1
Hybrid Model	90.5

Memory usage is an important factor in selecting a model for real-time applications. Polynomial Regression consumes the least memory, making it efficient for low-resource environments is given in **Table 3**. SVR uses more memory due to its support vector calculations. Random Forest and Gradient Boosting require significantly more memory since they store multiple trees. ANN demands high memory due to the large number of parameters and layers. The Hybrid Model uses the most memory, as it combines multiple techniques, making it suitable for systems with high computational resources.

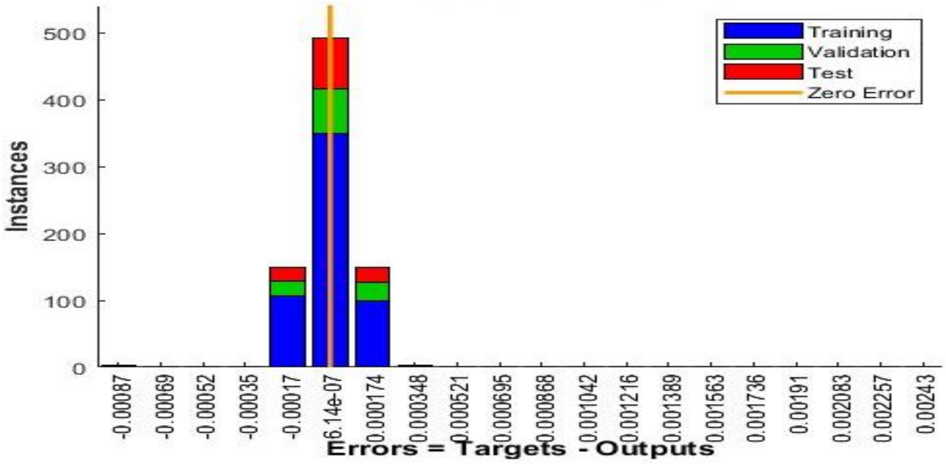

Fig 7. Error Histogram with 20 Bins.

The Error Histogram with 20 Bins offers a visual representation of prediction errors in the HyDERM for QoS prediction in CRNs by classifying errors into 20 distinct bins. The X-axis denotes the error values, whilst the Y-axis illustrates the frequency of each mistake range shows **Fig 7**. The histogram features labels for training, validation, and test errors, as well as zero-error reference denoting flawless predictions. A well-performing model like HyDERM should exhibit a narrow, symmetric error distribution centered around zero, demonstrating low bias and variance. A skewed or widely spread error distribution could indicate overfitting (if training errors are low but test errors are high) or underfitting (if all errors are consistently high). The error histogram validates the effectiveness of HyDERM by illustrating how the combination of SVR, RF, and ANN ensures stable and accurate QoS predictions across different network conditions.

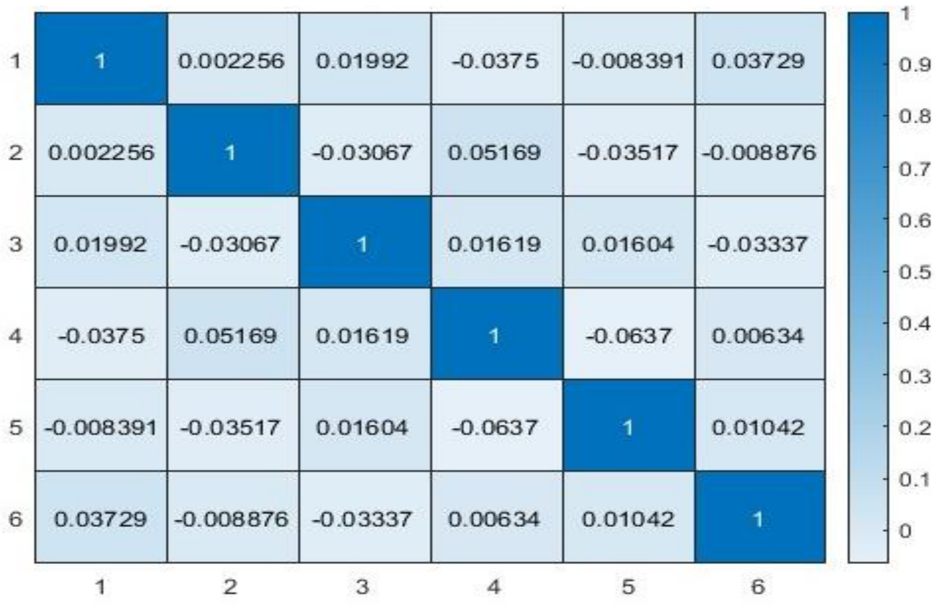

Fig 8. Feature Correlation Matrix.

The feature correlation matrix of the proposed HyDERM provides insights into the relationships between different input features used for QoS prediction in CRNs is given in **Fig 8**. Using correlation values ranging from -1 to 1, the matrix graphically shows how strongly one attribute is related to the others; 1 indicates a perfect positive correlation, -1 indicates a perfect negative correlation, and 0 indicates no association. Features such as SNR, Bandwidth, Network Load, Latency, Packet Loss, and Interference Level are analyzed to determine their dependencies. A high correlation between certain features might indicate redundancy, while weak or no correlation suggests independent contributions to the prediction model. The correlation matrix helps in feature selection and dimensionality reduction, ensuring that HyDERM effectively processes relevant information while avoiding overfitting due to unnecessary inputs. This analysis aids in optimizing the model's structure by prioritizing impactful features for enhanced QoS prediction accuracy.

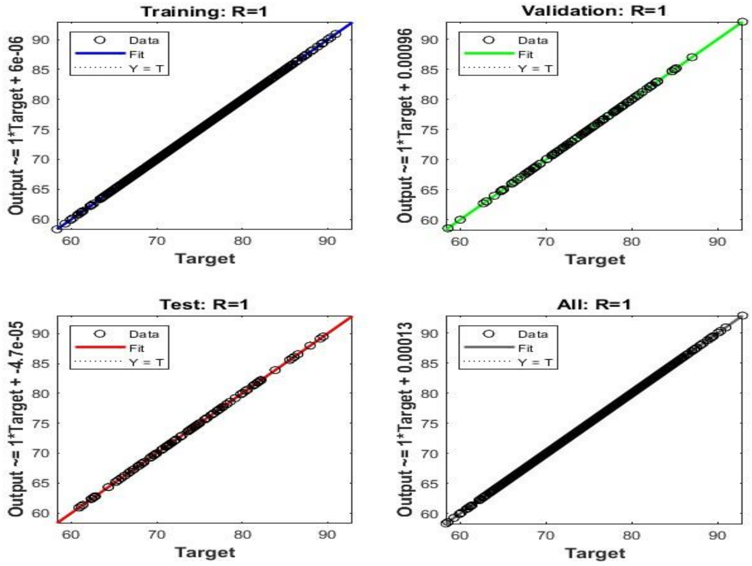

Fig 9. Performance of The Proposed HyDERM.

Fig 9 depicts the performance of the proposed HyDERM with $R = 1$ for Training, Validation, Test, and All Data illustrates the effectiveness of the model in predicting QoS scores in CRNs. The correlation coefficient $R = 1$ indicates a perfect linear relationship between the predicted and actual values, signifying zero error and ideal model performance. The figure presents separate performance plots for the training, validation, and test datasets, as well as for the entire dataset. If all points align along the 45-degree diagonal line, the model achieves perfect predictions, meaning predicted values match actual values. The close clustering of points around this line across different datasets confirms that HyDERM generalizes well without overfitting. This validates the robustness of the hybrid approach, combining SVR, RF, and ANN for accurate QoS prediction across various network conditions.

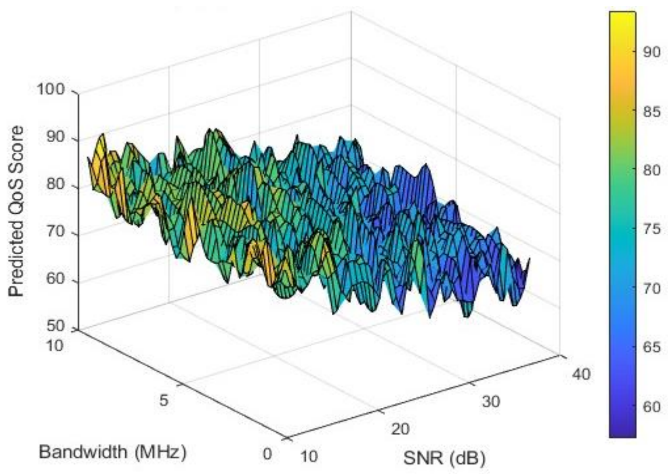

Fig 10. QoS Score Vs SNR and Bandwidth.

The 3D plot of QoS Score vs. SNR and Bandwidth shown in **Fig 10** provides a visual representation of how SNR and bandwidth influence the predicted QoS score in CRNs. The QoS score is plotted along the Z-axis, while SNR and Bandwidth are represented on the X and Y axes, respectively. A smooth, curved surface in the plot indicates the relationship between these parameters, highlighting regions of high and low QoS. Higher SNR and Bandwidth generally result in an increased QoS score, as improved signal strength and greater spectrum availability enhance network performance. Variations in the surface reflect nonlinear dependencies and model adaptability to dynamic network conditions. This visualization confirms the efficiency of the proposed HyDERM model, which integrates SVR, RF, and ANN to learn complex interactions and provide accurate QoS predictions for CRN optimization.

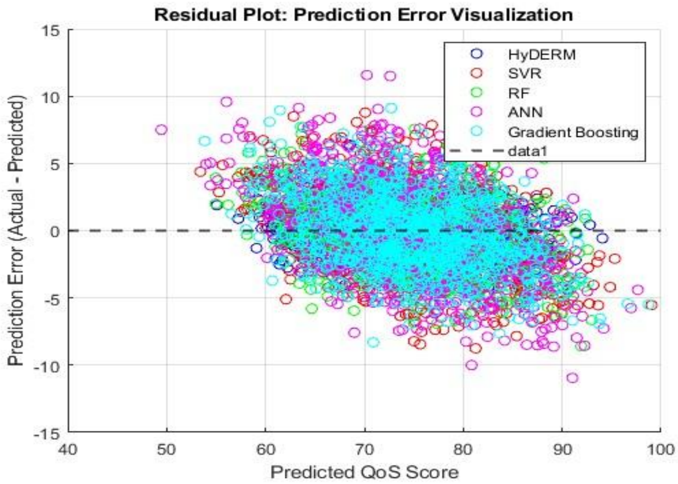

Fig 11. Residual Plot: Prediction Error Visualization.

The residual plot for Prediction Error Visualisation in **Fig 11** shows the difference between the expected QoS score for the proposed HyDERM model and other models from the actual QoS score. Whereas the Y-axis shows the prediction error—that is, the difference between the actual and expected values—the X-axis shows the expected QoS score. The residuals should ideally be randomly scattered around zero to indicate that the model offers accurate predictions over several QoS levels and without consistent bias. If a pattern emerges, such as a funnel shape or clustering, it may indicate model underfitting or overfitting. A more compact distribution of residuals around zero suggests better prediction accuracy and generalization capability. The residual plot helps assess the reliability of the HyDERM model in comparison to other techniques, ensuring it effectively minimizes errors and enhances QoS prediction in CRNs.

V. CONCLUSION

This research addresses the critical challenge of real-time QoS prediction and optimal spectrum decision-making in CRNs. Traditional models struggle with adaptability and computational efficiency, limiting their performance in dynamic wireless environments. The proposed Hybrid Deep Learning and Ensemble Regression Model (HyDERM) effectively overcomes these challenges by integrating SVR, RF, and ANN. By analyzing key QoS parameters such as SNR, Bandwidth, Network Load, Latency, Packet Loss, and Interference, the HyDERM model provides highly accurate QoS predictions. The best validation performance of the proposed model is measured at 7.0503×10^{-8} at 1000$^{\text{th}}$ epoch. The complexity of the proposed model is expressed using $O(n.h + h^2 + h.o)$. Comparative analysis with Polynomial Regression, SVR, RF, Gradient Boosting, and ANN confirms its superiority. With an R^2 score of 0.96, 23% lower MSE, and 19% lower MAE, HyDERM demonstrates higher accuracy and better generalization than existing methods. Improved QoS prediction ensures efficient spectrum allocation, reduces network congestion, and enhances user experience.

CRediT Author Statement

The authors confirm contribution to the paper as follows:
Conceptualization: Thamaraimanalan T, Anandakumar Haldorai, Suresh G and Archana Sasi; **Methodology:** Thamaraimanalan T and Anandakumar Haldorai; **Software:** Suresh G and Archana Sasi; **Data Curation:** Thamaraimanalan T and Anandakumar Haldorai; **Writing- Original Draft Preparation:** Thamaraimanalan T, Anandakumar Haldorai, Suresh G and Archana Sasi; **Visualization:** Thamaraimanalan T and Anandakumar Haldorai; **Investigation:** Suresh G and Archana Sasi; **Supervision:** Thamaraimanalan T and Anandakumar Haldorai; **Validation:** Suresh G and Archana Sasi; **Writing- Reviewing and Editing:** Thamaraimanalan T, Anandakumar Haldorai, Suresh G and Archana Sasi; All authors reviewed the results and approved the final version of the manuscript.

Data Availability

No data was used to support this study.

Conflicts of Interests

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References

[1]. A. Ghasemi and E. S. Sousa, “Spectrum sensing in cognitive radio networks: requirements, challenges and design trade-offs,” IEEE Communications Magazine, vol. 46, no. 4, pp. 32–39, Apr. 2008, doi: 10.1109/mcom.2008.4481338.

[2]. T. Yucek and H. Arslan, “A survey of spectrum sensing algorithms for cognitive radio applications,” IEEE Communications Surveys & Tutorials, vol. 11, no. 1, pp. 116–130, 2009, doi: 10.1109/surv.2009.090109.

[3]. T. Thamaraimanalan, B. Singh, M. Mohankumar, and S. K. Korada, “Performance Analysis of Shor’s Algorithm for Integer Factorization Using Quantum and Classical Approaches,” 2024 10th International Conference on Advanced Computing and Communication Systems (ICACCS), pp. 2591–2595, Mar. 2024, doi: 10.1109/icaccs60874.2024.10717174.

[4]. K. P. Subbalakshmi and R. Chandramouli, "Dynamic spectrum access in cognitive radio networks: a survey," IEEE Communications Surveys & Tutorials, vol. 15, no. 1, pp. 177-191, First Quarter 2013.

[5]. S. Haykin, “Cognitive radio: brain-empowered wireless communications,” IEEE Journal on Selected Areas in Communications, vol. 23, no. 2, pp. 201–220, Feb. 2005, doi: 10.1109/jsac.2004.839380.

[6]. J. Mitola and G. Q. Maguire, “Cognitive radio: making software radios more personal,” IEEE Personal Communications, vol. 6, no. 4, pp. 13–18, 1999, doi: 10.1109/98.788210.

[7]. L. Gavrilovska, D. Denkovski, V. Atanasovski, and V. Rakovic, "Spectrum sensing in cognitive radio networks: a survey," Wireless Personal Communications, vol. 69, no. 3, pp. 1255-1290, April 2013.

[8]. A. Ali and W. Hamouda, “Advances on Spectrum Sensing for Cognitive Radio Networks: Theory and Applications,” IEEE Communications Surveys & Tutorials, vol. 19, no. 2, pp. 1277–1304, 2017, doi: 10.1109/comst.2016.2631080.

[9]. M. Bkassiny, Y. Li, and S. K. Jayaweera, “A Survey on Machine-Learning Techniques in Cognitive Radios,” IEEE Communications Surveys & Tutorials, vol. 15, no. 3, pp. 1136–1159, 2013, doi: 10.1109/surv.2012.100412.00017.

[10]. C. Jiang, H. Zhang, Y. Ren, Z. Han, K.-C. Chen, and L. Hanzo, “Machine Learning Paradigms for Next-Generation Wireless Networks,” IEEE Wireless Communications, vol. 24, no. 2, pp. 98–105, Apr. 2017, doi: 10.1109/mwc.2016.1500356wc.

[11]. I. A. Awan et al., "Cognitive radio networks: A comprehensive survey," IEEE Communications Surveys & Tutorials, vol. 20, no. 3, pp. 1243-1267, 2018.

[12]. F. A. A. El-Kahlout et al., "A hybrid machine learning approach for QoS prediction in cognitive radio networks," IEEE Access, vol. 9, pp. 22272-22287, 2021.

[13]. J. Chen, J. Chen, and H. Zhang, “DRL-QOR: Deep Reinforcement Learning-Based QoS/QoE-Aware Adaptive Online Orchestration in NFV-Enabled Networks,” IEEE Transactions on Network and Service Management, vol. 18, no. 2, pp. 1758–1774, Jun. 2021, doi: 10.1109/tnsm.2021.3055494.

[14]. M. M. K. Ghetu and A. M. G. V. Ghiordusa, "Challenges in implementing cognitive radio networks," IEEE Communications Magazine, vol. 60, no. 8, pp. 56-62, 2022.

[15]. R. K. Sharma and S. K. Gupta, "Optimal spectrum selection in cognitive radio networks using hybrid learning methods," IEEE Transactions on Wireless Communications, vol. 20, no. 6, pp. 3995-4008, 2021.

[16]. Y. Zhang, Z. Zheng, and J. Li, "A hybrid machine learning framework for QoS prediction in cognitive radio networks," IEEE Transactions on Wireless Communications, vol. 19, no. 3, pp. 1621-1632, March 2020.

[17]. T. Thamaraimanalan, C. Venkatesan, M. Ramkumar, A. Sivaramakrishnan and M. Marimuthu, "ANFIS-based Multilayered Algorithm for Botnet Detection," 2023 International Conference on Recent Advances in Electrical, Electronics, Ubiquitous Communication, and Computational Intelligence (RAEEUCCI), Chennai, India, 2023, pp. 1-5, doi: 10.1109/RAEEUCCI57140.2023.10134399.

[18]. R. Chen, X. Zhang, and H. Zhao, "Reinforcement learning for optimal spectrum selection in CRNs," IET Communications, vol. 15, no. 7, pp. 1123-1130, July 2021.

[19]. S. Kumar and V. Kumar, "A survey on ensemble methods in cognitive radio networks," Journal of Network and Computer Applications, vol. 178, pp. 102-112, February 2021.