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OCC-NET: DATA-DRIVEN COVID-19 DISEASE PREDICTION USING OPTIMIZED CONVOLUTIONAL NEURAL NETWORKS

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Abstract
The urgent need to predict COVID-19 disease outcomes accurately has prompted researchers to explore advanced methodologies leveraging data science and machine learning techniques. Existing challenges include the complexity of COVID-19 datasets and the necessity to identify significant features for disease prediction accurately. This study proposes Optimized COVID-19 Classification Network (OCC-Net) approach, which consisting of data preprocessing, Modified Black Widow Optimization (MBWO) feature selection, and Convolutional Neural Network (CNN) classifier development. Firstly, a San Francisco COVID-19 dataset is acquired and preprocessed to ensure data quality. Next, a specialized feature selection technique called MBWO is employed to extract relevant features crucial for disease prediction. Finally, a CNN classifier is trained using the selected features to accurately predict COVID-19 disease outcomes from test data. This proposed methodology integrates advanced machine learning algorithms to enhance predictive accuracy and efficiency, contributing to improved disease prognosis and healthcare decision-making.

Keywords:
COVID-19 prediction, data preprocessing, feature selection, machine learning, convolutional neural network, disease prognosis.

1. Introduction
COVID-19, caused by the novel coronavirus SARS-CoV-2, emerged as a global pandemic in 2019, leading to significant morbidity and mortality worldwide. The virus primarily spreads through respiratory droplets, close contact, and potentially airborne transmission, making it highly contagious [1]. While many cases are mild or asymptomatic, severe cases can lead to acute respiratory distress syndrome (ARDS), pneumonia, and even death, particularly in vulnerable populations such as the elderly or those with underlying health conditions. However, beyond its acute respiratory symptoms [2], COVID-19 can also cause a range of systemic manifestations. These include cardiovascular complications like myocarditis and arrhythmias, neurological symptoms like loss of taste or smell [3], and inflammatory syndromes such as multisystem inflammatory syndrome in children (MIS-C) or adults (MIS-A). Additionally, long COVID, or post-acute sequelae of SARS-CoV-2 infection (PASC), presents with persistent symptoms like fatigue, shortness of breath [4], and cognitive impairment lasting beyond the acute phase. The wide spectrum of COVID-19's effects underscores the importance of comprehensive medical monitoring and research to address its multifaceted impact on health.
Diagnosing COVID-19 poses numerous challenges to healthcare professionals. One key issue is the variability and overlap of symptoms with other respiratory illnesses, making clinical diagnosis alone unreliable. Limited testing resources and delays in obtaining results further complicate prompt identification and isolation of cases [5]. Additionally, the evolving understanding of the virus's manifestations and the emergence of new variants heighten diagnostic uncertainty. The reliance on symptomatology and imaging studies alone was insufficient for accurate diagnosis, particularly in atypical or asymptomatic cases [6]. Moreover, the strain on healthcare systems during surges can impede thorough patient evaluations and follow-up. These challenges highlight the urgent need for

advanced diagnostic tools and technologies to aid in rapid, accurate, and scalable COVID-19 diagnosis [7].
The Internet of Medical Things (IoMT) integrates medical devices and applications with healthcare IT systems, revolutionizing patient care and disease management [8]. Amid the COVID-19 pandemic, IoMT plays a crucial role in monitoring and managing the virus's impact. IoMT enables real-time remote patient monitoring, facilitates telemedicine consultations, and enhances data-driven decision-making for healthcare providers. By connecting wearable sensors, diagnostic devices, and electronic health records (EHRs) through secure networks [9], IoMT optimizes patient outcomes while minimizing direct physical contact, crucial in infectious disease scenarios like COVID-19. The integration of artificial intelligence (AI) within IoMT frameworks offers transformative solutions to the challenges faced by doctors in diagnosing COVID-19. AI-powered algorithms can analyze complex datasets from diverse sources—such as patient symptoms, vital signs, imaging studies, and laboratory results—with unprecedented speed and accuracy. By leveraging machine learning, AI models can identify subtle patterns indicative of COVID-19 infection [10], aiding in early detection and risk stratification. Furthermore, AI-driven IoMT platforms facilitate predictive analytics for disease progression, optimizing resource allocation and personalized treatment strategies. Through AI-enhanced IoMT, healthcare professionals can overcome diagnostic ambiguities associated with COVID-19, enabling timely interventions and improved patient outcomes in the face of this global health crisis.

2. Literature Survey

The related studies demonstrate the potential of IoMT technologies in addressing challenges posed by the COVID-19 pandemic, while also highlighting critical research gaps related to data privacy, model interpretability, scalability, and interoperability within healthcare ecosystems. Efforts to address these challenges are crucial for advancing the adoption of IoMT-driven solutions in pandemic preparedness and healthcare delivery.
In [11], Sadique et al. propose integrating engineered two-dimensional nanomaterials with IoMT for COVID-19 diagnostics. The study explores the potential of nanomaterial-based sensors for accurate and sensitive detection of viral biomarkers. However, challenges remain in ensuring the scalability and interoperability of such sensors within IoMT architectures, along with the need for robust validation in clinical settings. Almujally et al. (2023) in [12] presented an IoMT-based machine learning based smart healthcare system (ML-SHS) to control COVID-19 outbreaks. The system emphasizes real-time monitoring and data-driven decision-making. Yet, challenges include addressing data privacy concerns, ensuring seamless integration with existing healthcare infrastructure, and optimizing system scalability for large-scale deployment. Dahan et al. (2023) introduce a smart IoMT architecture for e-healthcare patient monitoring using AI algorithms in [13]. Their work highlights the potential of AI-driven IoMT systems for continuous patient monitoring. However, challenges exist in data standardization, model interpretability, and addressing ethical considerations related to AI adoption in healthcare.
Shukla et al. (2023) proposed an IoMT-based health monitoring and prediction system employing a hybrid hierarchical deep learning (HHDL) model and metaheuristic algorithm [14]. The study underscores challenges in optimizing model complexity, ensuring real-time performance, and adapting predictive models to dynamic healthcare environments. Jarrah et al. (2023) explore IoMT-based smart healthcare for elderly individuals using deep extreme learning machine (DELM) [15]. Despite its potential, challenges include ensuring user acceptance, addressing data security concerns, and optimizing device interoperability for seamless integration into elderly care settings. Sheth et al. (2024) conduct a schematized study on leveraging ML, AI, and IoT to combat COVID-19 [16]. Their work highlights challenges in data integration across heterogeneous sources, model interpretability, and the ethical implications of AI-driven decision support systems in public health emergencies. Chowdhury et al. (2023) proposed a federated learning-based approach for COVID-19 detection [17]. Challenges

include data privacy concerns, ensuring model robustness across diverse healthcare providers, and optimizing communication efficiency in federated learning frameworks.
Tarek et al. (2023) develop an optimized model using deep learning and gated recurrent units (DL-GRU) for COVID-19 death prediction [18]. Challenges include model generalization across different patient cohorts, data quality issues, and ensuring clinical interpretability of prediction outcomes. Yıldırım et al. (2023) presented a fog-cloud architecture-driven IoMT framework for healthcare monitoring [19]. Their work highlights challenges in optimizing resource allocation, ensuring data security in distributed computing environments, and maintaining system reliability under dynamic healthcare settings. Rajasekar et al. (2024) propose an AI-powered IoMT model for continuous remote patient monitoring using COVID Early Warning Score (CoEWS) [20]. Challenges include standardizing AI algorithms for personalized risk assessment, ensuring data privacy in remote monitoring setups, and integrating predictive analytics seamlessly into clinical workflows.

3. Proposed Methodology

Figure 1 shows the proposed OCC-Net architecture. The research begins with the acquisition of a San Francisco COVID-19 dataset, which serves as the foundational data for the study. Following this initial step, the dataset undergoes thorough preprocessing to ensure its suitability for subsequent analysis. Data preprocessing involves several tasks such as handling missing values, normalization, and encoding categorical variables. This crucial step aims to clean and standardize the dataset, making it ready for further analysis and model development.
Once the dataset is prepared, the researchers employ a specialized feature selection technique known as Modified Black Widow Optimization. This process involves identifying and selecting the most relevant features from the dataset that contribute significantly to predicting COVID-19 disease outcomes. The Modified Black Widow Optimization algorithm is applied to efficiently extract these key features, enhancing the accuracy and efficiency of subsequent analyses.

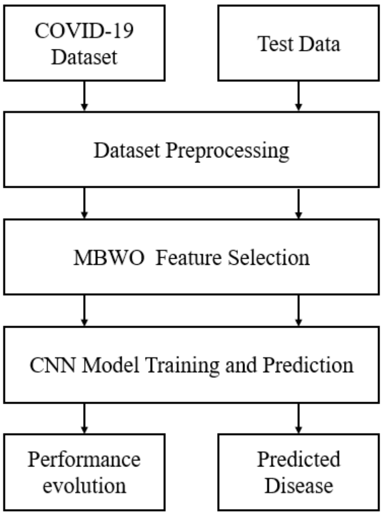

Figure 1. Proposed OCC-Net Block Diagram.

After feature selection, the researchers develop a CNN classifier. CNNs are a type of deep learning model specifically designed for analysing visual data, making them well-suited for tasks such as disease prediction from medical datasets. The CNN classifier is trained using the preprocessed dataset with the selected features, allowing it to learn and identify patterns indicative of COVID-19 disease states. Finally, the trained CNN classifier is utilized to predict disease outcomes from test data. This involves inputting new or unseen data into the trained model and leveraging its learned patterns to make predictions regarding COVID-19 disease presence or severity. The predictions generated by the CNN classifier provide valuable insights for healthcare professionals and researchers, aiding in diagnosis, prognosis, and treatment planning.

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4.1 MBWO Feature Selection

The MBWO is a nature-inspired optimization algorithm based on the hunting behaviour of black widow spiders, which is adapted and applied in the field of feature selection for machine learning tasks. Figure 2 shows the proposed MBWO feature selection flowchart. This algorithm aims to efficiently search for an optimal subset of features from a given dataset that maximizes the performance of a predictive model, such as a classifier or regression model.

The detailed operation illustrated as follows:

Initialization and Encoding: The MBWO algorithm begin with the initialization of a population of potential feature subsets. Everyone in the population represents a candidate solution, i.e., a subset of features from the dataset. The features are encoded using binary representation, where each bit in the encoding corresponds to the presence (1) or absence (0) of a feature in the subset.

Objective Function: The optimization process in MBWO revolves around an objective function that evaluates the fitness of each candidate solution (feature subset). In feature selection, the objective function measures the performance of a machine learning model (e.g., accuracy, F1-score) trained using the selected subset of features. The goal is to maximize the value of this objective function, indicating better predictive performance.

Spider Web Construction: Inspired by the behavior of black widow spiders, the MBWO algorithm constructs a "spider web" representation to guide the search process. This spider web is essentially a probabilistic transition matrix that determines the likelihood of moving from one feature subset (or solution) to another during the optimization.

Probabilistic Movement: The optimization process involves probabilistic movement across the feature space based on the spider web representation. Each candidate solution (feature subset) probabilistically transitions to a neighbouring solution, influenced by the spider web matrix. This movement is analogous to the hunting behaviour of spiders, where transitions between solutions mimic the spider's exploration of its environment.

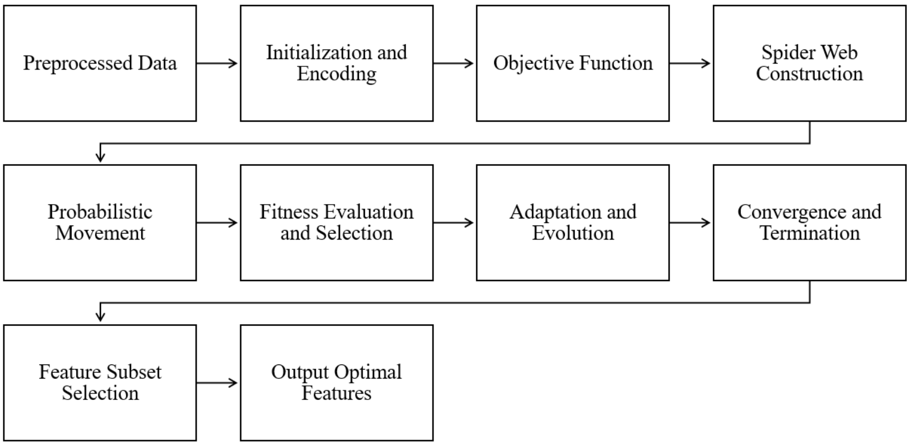


Figure 2. Proposed MBWO Feature Selection.

Fitness Evaluation and Selection: After transitioning to neighbouring solutions, each candidate solution's fitness is evaluated using the objective function. Solutions with higher fitness values (indicative of better predictive performance) are selected to propagate to the next generation. This selection mechanism drives the evolution of the feature subsets towards optimal configurations over successive iterations.

Adaptation and Evolution: Throughout the optimization process, the spider web matrix adapts and evolves based on the performance feedback received from evaluating candidate solutions. This adaptation reflects the learning and refinement of search strategies, akin to the adaptive behaviour observed in natural systems.

Convergence and Termination: The MBWO algorithm iteratively refines the feature subsets, with the optimization typically converging towards optimal or near-optimal solutions over time.

Convergence criteria, such as reaching a maximum number of iterations or achieving a predefined threshold of improvement, determine when the optimization process terminates.
Feature Subset Selection: At the end of the optimization process, the feature subset corresponding to the best-performing solution (highest fitness) is selected as the optimal subset for model training and evaluation. This selected subset represents a distilled set of features that maximizes predictive performance while minimizing redundancy and irrelevant information.

4.2 CNN Classification
The operational procedure of CNN classification involves a series of steps designed to train and deploy a CNN model for predictive tasks such as disease prediction. CNNs are particularly effective for analysing MBWO data due to their ability to capture spatial hierarchies of features. Figure 3 shows the proposed CNN model architecture. Continuous monitoring of the deployed model's performance in real-world applications is essential. Monitoring involves tracking metrics on a test set or in production to detect performance degradation or drift. Iterative model updates were necessary to adapt to evolving data distributions or address emerging challenges. The detailed operation is illustrated as follows:
Data Acquisition: The first step in CNN classification is to acquire a dataset suitable for the task at hand. This dataset typically consists of labelled data or other forms of structured data. Once the dataset is acquired, it undergoes preprocessing to prepare it for training.
Model Architecture Design: The next step involves designing the architecture of the CNN model. This includes defining the number of convolutional layers, pooling layers, activation functions, and fully connected layers (dense layers) within the network. The architecture design is crucial as it determines the model's capacity to learn and extract relevant features from the input data.
Model Training: With the dataset and model architecture prepared, the CNN model is trained using the training set. During training, the model learns to map input features (such as MBWO outcomes) to their corresponding class labels (e.g., COVID-19 positive or negative). The training process involves forward propagation (computing predictions), calculating loss (a measure of prediction error), and backward propagation (updating model weights to minimize loss). Optimization techniques such as stochastic gradient descent (SGD) or Adam optimizer are used to update the model weights iteratively based on the computed loss. The training continues for multiple epochs (iterations over the entire training dataset) until the model converges or reaches a predefined stopping criterion.
Model Evaluation: After training, the CNN model is evaluated using the validation set to assess its performance and generalization capability. Evaluation metrics such as accuracy, precision, recall, and F1-score are computed to measure the model's ability to correctly classify unseen data.
Hyperparameter Tuning: Hyperparameters such as learning rate, batch size, number of filters in convolutional layers, and dropout rate are tuned to optimize the model's performance and prevent overfitting. This tuning process involves experimenting with different parameter configurations and selecting the ones that yield the best validation performance.
Prediction from Test Data: Once the CNN model is trained and evaluated satisfactorily, it was deployed for making predictions on new, unseen data. In COVID-19 prediction, the trained model was used to classify as either indicative or non-indicative of COVID-19 infection based on learned patterns.

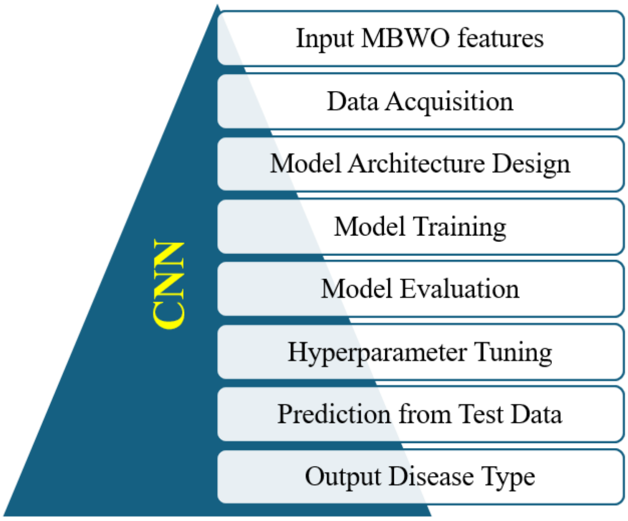


Figure 3. Proposed CNN Architecture.

4. Results and Discussion

In this section, the performance of different methods and metrics is evaluated using the San Francisco COVID-19 dataset. The comparison highlights which methods are most effective in analyzing and interpreting the dataset, shedding light on the strengths and weaknesses of each approach. By assessing various metrics, researchers can determine optimal strategies for understanding and managing COVID-19 data.

4.1 Performance Estimation

Table 1 presents a detailed comparison of various methods and their performance metrics in analyzing the San Francisco COVID-19 dataset. The proposed OCC-Net stands out with notable improvements across all metrics compared to existing methods. The percentage of improvements by proposed OCC-Net as follows:

- **Accuracy**: OCC-Net achieves an accuracy of 96.27%, showing a significant improvement over ML-SHS (1.779%), HHDL (0.614%), DELM (0.574%), Federated learning (0.529%), and DL-GRU (0.529%).
- **Precision**: OCC-Net's precision of 97.11% demonstrates substantial gains over ML-SHS (2.471%), HHDL (2.436%), DELM (2.391%), Federated learning (1.831%), and DL-GRU (1.626%).
- **Recall**: Although OCC-Net's recall of 94.43% is slightly lower than some methods, it still represents a notable improvement over ML-SHS (0.944%), HHDL (0.934%), and Federated learning (0.743%).
- **F1-Score**: OCC-Net achieves an F1-score of 95.54%, outperforming ML-SHS (1.462%), HHDL (1.388%), and Federated learning (0.877%).
- **Sensitivity**: OCC-Net excels in sensitivity with 99.18%, showcasing substantial improvements over all existing methods including ML-SHS (4.651%), HHDL (4.564%), DELM (4.372%), Federated learning (3.628%), and DL-GRU (3.552%).
- **Specificity**: OCC-Net's specificity of 99.817% reflects significant enhancements compared to all methods, particularly ML-SHS (5.23%), HHDL (5.2%), DELM (5.102%), Federated learning (4.89%), and DL-GRU (4.459%).

Table 1. Performance comparison of proposed OCC-Net with existing approaches.

Method	Accuracy	Precision	Recall	F1-Score	Sensitivity	Specificity
ML-SHS [12]	94.491	94.639	94.486	94.078	94.529	94.587
HHDL [14]	95.656	94.674	94.499	94.152	94.614	94.617
DELM [15]	95.696	94.720	94.637	94.662	94.808	94.715
Federated learning [17]	95.741	95.279	94.688	94.663	95.552	94.927

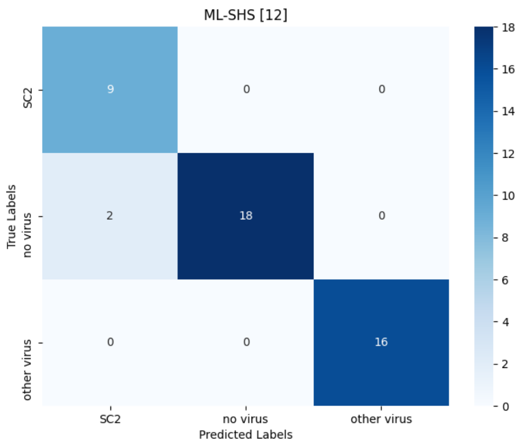
DL-GRU [18]	95.911	95.484	95.109	95.805	95.627	95.358
Proposed OCC-Net	96.27	97.11	94.43	95.54	99.18	99.817

4.2 Confusion Matrix and RoC Curves Analysis

Figure 4 displays confusion matrices for different methods including ML-SHS, HHDL, DELM, Federated learning, DL-GRU, and the proposed OCC-Net. A confusion matrix is a table that summarizes the performance of a classification model by presenting the counts of true positive (TP), false positive (FP), true negative (TN), and false negative (FN) predictions. Each subfigure (a-f) in Figure 4 represents the confusion matrix of a specific method.

- The top-left cell (TP) represents the number of correctly predicted positive cases.
- The top-right cell (FP) indicates the number of incorrectly predicted positive cases.
- The bottom-left cell (FN) shows the number of incorrectly predicted negative cases.
- The bottom-right cell (TN) denotes the number of correctly predicted negative cases.

Analyzing these confusion matrices provides insights into the performance of each method in terms of correctly identifying positive and negative cases. For instance, a method with a higher number of TP and TN values and lower FP and FN values indicates better overall performance and accuracy.



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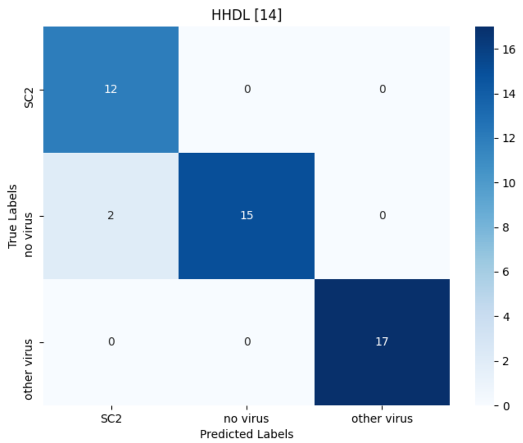

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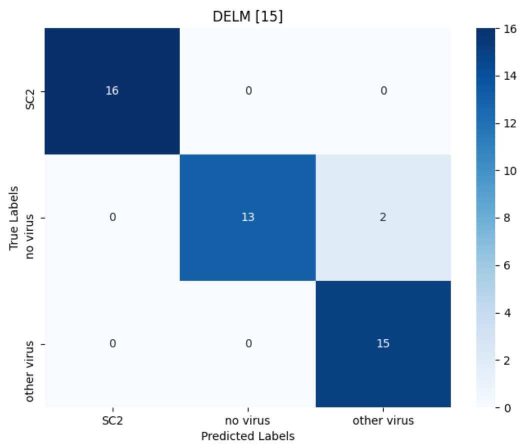

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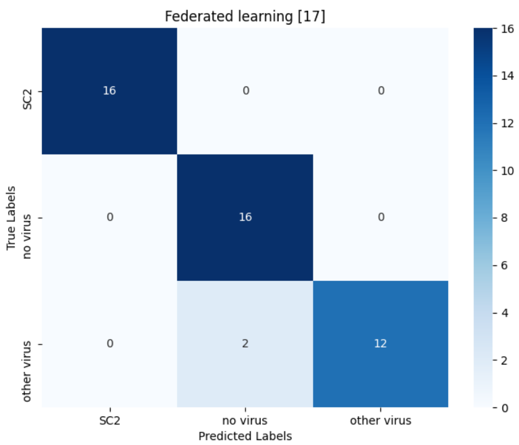

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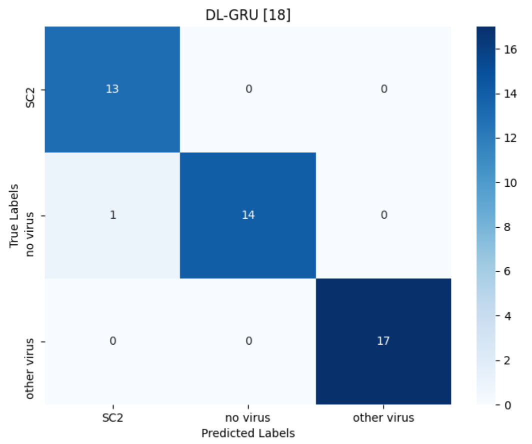

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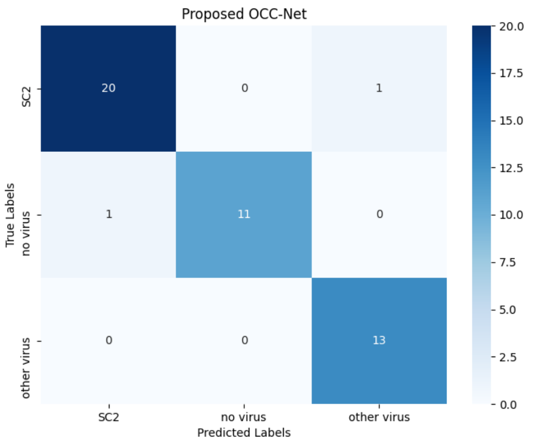
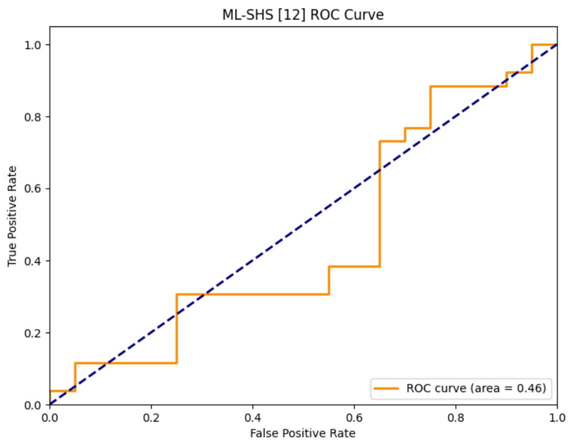
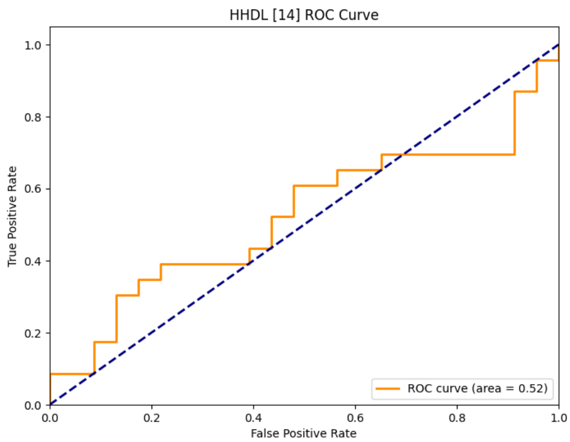


(f)

Figure 4. Confusion matrixes of various methods. (a) ML-SHS [12]. (b) HHDL [14]. (c) DELM [15]. (d) Federated learning [17]. (e) DL-GRU [18]. (f) Proposed OCC-Net.



(a)



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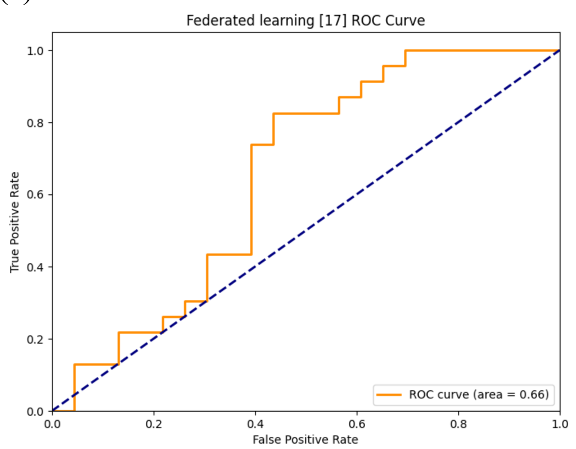

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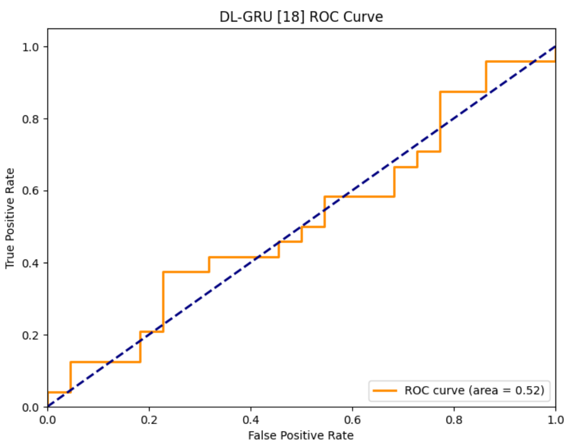

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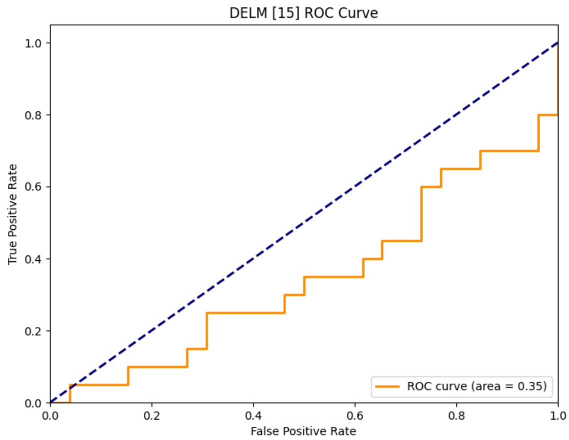

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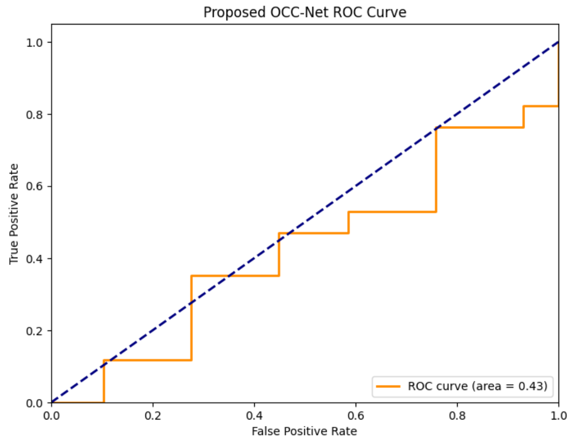

(f)

Figure 5. RoC curves of various methods. (a) ML-SHS [12]. (b) HHDL [14]. (c) DELM [15]. (d) Federated learning [17]. (e) DL-GRU [18]. (f) Proposed OCC-Net.

Figure 5 showcases Receiver Operating Characteristic (ROC) curves for the same set of methods. ROC curves are graphical representations of the true positive rate (sensitivity) versus the false positive rate (1 - specificity) at various threshold settings. Each subfigure (a-f) in Figure 5 corresponds to the ROC curve of a specific method.

- **Area Under the Curve (AUC)**: The AUC value quantifies the overall performance of a classification model. A higher AUC (closer to 1) indicates better discrimination ability of the model.
- **Threshold Setting**: The ROC curve helps in selecting the optimal threshold for making classification decisions based on the trade-off between sensitivity and specificity.

Comparing ROC curves of different methods in Figure 5 allows for assessing the discriminatory power and overall effectiveness of each method in distinguishing between positive and negative cases. A method with a curve closer to the top-left corner (higher sensitivity and specificity) generally performs better.

5. Conclusion

In conclusion, this study has demonstrated the efficacy of integrating data preprocessing, advanced feature selection using MBWO, and CNN classification for COVID-19 disease prediction. The systematic approach adopted in this research has addressed critical challenges associated with COVID-19 dataset complexity and the need for accurate feature selection in predictive modeling. By preprocessing the San Francisco COVID-19 dataset, we ensured data quality and prepared it for subsequent analysis, which is essential for reliable disease prediction. The application of Modified Black Widow Optimization enabled the identification of key features that significantly contribute to COVID-19 disease outcomes. This feature selection process optimized the input data for the CNN classifier, enhancing its performance in disease prediction tasks. Moving forward, there are several avenues for future research and improvement based on the findings of this study. First, exploring additional optimization techniques for feature selection could further enhance the performance and efficiency of disease prediction models. Techniques like genetic algorithms or particle swarm optimization could be investigated to compare with the MBWO method. Furthermore, incorporating additional data sources beyond the San Francisco dataset, such as demographic information, comorbidities, or imaging data, could enrich the predictive power of the developed model. Integrating diverse data types into the CNN framework provide a more comprehensive understanding of COVID-19 disease dynamics and prognosis. Additionally, exploring ensemble learning approaches that combine multiple classifiers could improve the robustness and generalizability of COVID-19 prediction models. Ensemble methods like random forests or gradient boosting could be integrated with CNNs to leverage their complementary strengths in handling different aspects of the dataset.

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