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Deep Neural Ensemble Classification for COVID-19 Dataset

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The COVID-19 pandemic has necessitated the development of accurate and efficient classification models for diagnosis and prognosis. While deep learning has shown promising results in various medical applications, its combination with ensemble methods, which amalgamate the predictions of multiple classifiers, can further enhance the model's accuracy. This research paper introduces a novel approach called Deep Neural Ensemble Classification (DNEC) to tackle the challenge of Developing an enhanced ensemble model using deep learning algorithms and comparing its performance with existing ensemble methods. The research problem stems from the literature gap, where existing studies primarily focus on single-model approaches, lacking in-depth exploration of ensemble methods for COVID-19 classification. Motivated by the potential improvement in classification accuracy through ensemble methods, this study aims to create a deep neural ensemble classification model to improve the classification accuracy tailored for COVID-19 data. A set of diverse classifiers, including k-nearest neighbour (IBK), decision tree (J48), naïve bayes (NB), support vector machine (SVM), and sequential minimal optimization (SMO), are utilized in the proposed ensemble method. The accuracy improvement of the ensemble classifiers is evaluated using various metrics such as precision, recall, F1 score, confusion matrix, and processing time. The proposed method demonstrates that IBK+SVM+NB emerges as the top-performing deep neural ensemble classifier with an accuracy score of 99.29% and a total run time of 27.61 seconds. The innovative ensemble techniques introduced in this research contribute to the existing body of knowledge by filling the identified literature gap and offering a novel and highly accurate approach for COVID-19 classification.

Keywords: Deep learning, COVID-19, Deep Neural Ensemble Classification, SVM, SMO.

1. Introduction

The COVID-19 pandemic, caused by the novel coronavirus SARS-CoV-2, has profoundly impacted global health, economies, and daily life [1]. Since its emergence in late 2019, researchers and healthcare professionals have been striving to understand its transmission dynamics, clinical manifestations, and effective diagnostic and therapeutic strategies. Accurate and timely diagnosis of COVID-19 is paramount, not only for patient care but also for controlling the spread of the virus [2]. In this context, computational models, particularly those based on deep learning, have emerged as powerful tools in assisting medical professionals with diagnosis and prognosis.

Ensemble classification is a machine learning paradigm that combines multiple classifiers to produce a final decision, often yielding better performance than any individual classifier [3,4]. The principle behind ensemble classification is that by leveraging the strengths of diverse models, one can achieve a more robust and accurate classification. This approach has been successfully applied in various domains, from finance to image recognition. The classification of COVID-19 cases presents a multifaceted task due to the variability in symptoms, the evolution of the virus, and the presence of confounding factors in the datasets. To tackle this complexity, the research investigates the concept of ensemble learning. This approach capitalizes on the diversity of classifiers, reducing overfitting and improving overall performance. Ensemble methods have emerged as powerful tools in enhancing the accuracy and generalizability of machine learning models [5].

Deep learning, a subset of machine learning, has gained significant attention in recent years due to its capacity to process vast amounts of data and extract intricate patterns [6]. Deep Neural Networks (DNNs), the cornerstone of deep learning, are composed of multiple layers of interconnected nodes that can automatically learn representations from data. Their ability to handle complex data structures makes them particularly suitable for medical applications, where data can be multifaceted and heterogeneous. Modelled after the intricate structure of the human brain, DNNs utilize multiple layers of interconnected nodes to extract hierarchical representations from input data. This architecture has exhibited exceptional performance in tasks ranging from image and speech recognition to natural language processing.

When deep learning is combined with ensemble methods, the potential for accuracy enhancement is substantial. The fusion of deep neural networks with ensemble classification can harness the depth and complexity of DNNs while benefiting from the robustness of ensemble techniques. However, despite the promise of this combination, there is a noticeable gap in the literature regarding ensemble approaches based on deep learning algorithms for COVID-19 classification.

The novelty of this research lies in introducing the Deep Neural Ensemble Classification (DNEC) approach, specifically tailored for COVID-19 datasets. Motivated by the potential to significantly improve classification accuracy and address the existing literature gap, the primary objective of this research is to create and evaluate a deep neural ensemble classification model for COVID-19 data.

The remainder of this paper is organized as follows: Section 2 provides a detailed review of related works in ensemble classification, deep learning, and their applications in medical diagnosis. Section 3 describes the methodology, including data preprocessing, model architecture, and evaluation metrics. Section 4 presents the experimental results and discussions. Finally, Section 5 concludes the paper with key findings, implications, and potential directions for future research.

2. Literature Review

2.1 Ensemble Methods

Ensemble methods operate on the principle of aggregating the predictions from multiple base models to produce a final prediction that is often more accurate and robust than the predictions of individual models [7,8]. Various techniques such as bagging, boosting, and stacking have been developed to implement ensemble methods, each with unique characteristics and applications [9,10]. Bagging helps in reducing overfitting by training individual models on random subsets of the data [11], while boosting focuses on training models sequentially to correct the mistakes of previous models [12]. Stacking, on the other hand, combines predictions from different models using another model, often referred to as a meta-model [13].

In the medical field, ensemble methods have shown remarkable success in various applications such as cancer diagnosis, heart disease prediction, and more recently, in the classification of COVID-19 cases [14]. The integration of ensemble methods with medical data has led to improved predictive performance, enabling healthcare professionals to make more informed decisions. For instance, a study by [3] demonstrated that ensemble methods outperformed single-model approaches in predicting patient readmissions, underscoring the potential of these techniques in enhancing healthcare outcomes. The application of ensemble methods to COVID-19 classification represents a natural extension of this trend, opening new avenues for research and innovation in pandemic response.

2.2 Deep Learning in Medical Diagnosis

Artificial Neural Networks (ANNs) with multiple hidden layers, known as Deep Neural Networks (DNNs), are designed to learn complex nonlinear relationships between input and output data [8]. These networks are commonly used in supervised machine learning and have proven to be effective for handling large amounts of data, achieving high levels of accuracy [15]. Deep learning algorithms have revolutionized medical diagnosis by enabling the automated analysis of intricate medical data, such as medical imaging and genomic information. From image recognition in radiology to predictive modeling in personalized medicine, deep learning has shown promising results in various medical applications, including COVID-19 classification [16–20]

However, despite the advantages, deep learning models can be computationally intensive, requiring significant processing power and memory resources[21,22]. Additionally, these models may require extensive tuning and hyperparameter optimization to perform optimally, presenting limitations in certain scenarios, especially in resource-constrained environments. The complexity of deep learning models also raises concerns about interpretability and transparency, as understanding the decision-making process within deep neural networks can be challenging. These limitations highlight the need for continued research and innovation in the field, balancing the power and potential of deep learning with practical considerations and ethical implications.

2.3 Ensemble Based on Deep Learning Algorithm

The integration of deep learning with ensemble methods represents a cutting-edge approach in machine learning, offering the potential to significantly enhance classification performance [23]. Deep learning algorithms, characterized by their ability to automatically learn hierarchical representations from raw data, have shown remarkable success in various domains, including image recognition, natural language processing, and medical diagnosis [24]. Ensemble methods, on the other hand, leverage the collective intelligence of multiple classifiers to improve prediction accuracy and robustness.

The synergy between deep learning and ensemble methods has been explored in different contexts. For instance, [25] proposed an ensemble of deep neural networks for image classification, demonstrating improved accuracy over single-model approaches. Similarly, [26,27] utilized an ensemble of deep learning models for cancer detection, achieving higher accuracy results.

However, the specific application of deep learning-based ensemble methods to COVID-19 classification remains an underexplored area. Existing studies on COVID-19 classification have either focused on traditional ensemble methods without deep learning integration [28] or single-model deep learning approaches [29,30], leaving a significant gap in the literature.

The novel contribution of this research lies in developing a Deep Neural Ensemble Classification (DNEC) method tailored for COVID-19 data. By amalgamating the predictive power of deep neural networks with the robustness of ensemble techniques, the proposed method aims to achieve unparalleled accuracy in COVID-19 classification. This innovative approach fills a critical void in the current body of knowledge and offers a promising direction for future medical diagnosis and prognosis research.

2.4 Existing Ensemble and Deep Learning Approaches for COVID-19 Classification

The application of ensemble methods in COVID-19 classification has been explored by various researchers, often focusing on traditional machine learning algorithms. For example, [31] combined KNN, decision tree, logical regression, SVM, and NB classifiers to create an ensemble model, achieving an accuracy of 98.6% on a specific COVID-19 dataset. However, their approach did not integrate deep learning techniques, leaving potential areas for improvement [31]. On the other hand, deep learning has been employed as a standalone approach in COVID-19 classification. [32] utilized Convolutional Neural Networks (CNNs) to classify COVID-19 chest X-rays, achieving a precision of 99.31%. While their model demonstrated high precision, it did not explore the synergistic effects of combining deep learning with other classifiers, indicating a gap in the literature.

In contrast to these separate approaches, some studies have begun to explore integrating deep learning within ensemble methods for COVID-19 classification. For instance, [33-41] proposed a hybrid ensemble model that combined deep learning with traditional classifiers like K-Nearest Neighbors, Support Vector Machine (Linear and RBF), Naive Bayes, Decision Tree, Random Forest, MultiLayer Perceptron, AdaBoost, ExtraTrees, Logistic Regression, Linear and Quadratic Discriminant Analysis (LDA/QDA), Passive, Ridge, and Stochastic Gradient Descent Classifier. Their method achieved a 99.28% mean accuracy score, demonstrating the potential benefits of this integrated approach. However, the literature still lacks a comprehensive exploration of deep neural ensemble classification specifically tailored for COVID-19 data. The existing studies primarily focus on either deep learning or ensemble methods, with limited research combining the strengths of both. This gap in the literature underscores the need for further research and innovation in developing ensemble models that fully leverage deep learning algorithms for COVID-19 classification, a challenge that the present study aims to address.

3. Methodology

Figure 1. Framework for Deep Neural Ensemble Classification Algorithm on COVID-19 datasets

3.1 Data collection

The COVID-19 dataset utilized in this study was sourced from the Kaggle Website, specifically under the heading "Symptoms and COVID Presence (May 2020 data)." Hemanth Harikrishnan, following the guidelines set by WHO, crafted this dataset in India during March 2020. It encompasses all conceivable symptoms related to COVID-19, aiding in the forecasting of the virus's likely presence. This dataset is structured with 20 distinct features, each representing a possible symptom, and one class attribute to ascertain the presence or absence of COVID-19. The class label is divided into two categories: "Yes," indicating the presence of COVID-19, and "No," signifying its absence.

Comprising 5434 instances, some of which may contain missing values, the dataset provides a comprehensive overview of the attributes and their descriptions, as laid out in Table 2. Each attribute is classified into either 'Yes' or 'No,' with 'Yes' denoting the existence of the symptoms and 'No' marking their nonexistence.

3.2 Data pre-processing

The COVID-19 dataset classification begins with the application of pre-processing techniques to transform raw data into a comprehensible format, enhancing accuracy. This process includes handling missing values, removing outliers and extreme values, discretizing data, and extracting features. For instance, missing instances under the 'Hyper Tension' attribute were eliminated using WEKA tools' 'ReplaceMissingValues' filter.

Since the dataset was nominal, no data discretization was required. Outliers and extreme values were identified and removed using the InterquartileRange filter, specifically for instances labeled "Yes". The dataset's class balance ratio of approximately 4:1 between Positive and Negative classes was significantly imbalanced, potentially affecting the model's performance. To mitigate this, techniques like undersampling the majority class and oversampling the minority class were employed using the SpreadSubsample filter and SMOTE filter. These measures helped balance the dataset, promoting better overall model performance.

3.3 Feature Selection

In the research conducted, the WrapperSubsetEval technique was utilized as a feature assessment method, and the BestFirst approach was employed for searching, all within the context of Weka. The WrapperSubsetEval technique assesses the effectiveness of feature subsets by gauging the accuracy or error percentage of a specific classifier on the chosen attributes. On the other hand, the BestFirst search technique integrates both forward and backward search tactics, evaluating feature subsets by either incorporating or eliminating individual features sequentially.

3.4 Single Classification

Initially, the classification process is carried out with a single base classifier, employing a 10-fold cross-validation method to construct the model. This method involves dividing the data into 10 equal parts or folds. It's a widely accepted technique due to its simplicity and tendency to provide a more unbiased or less optimistic evaluation of the model's ability compared to other methods like a straightforward train/test split. In the beginning, the classifiers were trained and evaluated using the original, unbalanced dataset before selecting features. Afterwards, feature selection was conducted through the WrapperSubsetEval attribute evaluator and the BestFirst search technique. The chosen features were then utilized to train and test the classifiers, with the accuracy scores being documented. The classifier's top accuracy score was selected for further examination and comparison. Subsequently, this model was employed as a measure for the next phase.

3.5 Deep Neural Ensemble Classification

3.5.1 Combination Generation Algorithm

In the ensemble method, we utilize a deep neural network approach to combine the outputs of various classifiers. The combination generation algorithm serves as the rule for combining prediction class results. This algorithm leverages the Itertools library in Python to generate all possible combinations of classifiers. The classifiers are initialized as N=['IBK','J48','SVM','SMO','NB'], and the algorithm iteratively explores all possible combinations of these classifiers, printing each combination. The process is illustrated in the following pseudocode:

Start

    Importing Combinations function from Itertools;

    Initialize N;

```
    for i in range 1 to length of N+1;
        for combination in Combinations(N,i);
            print combination;
    Check all possible combinations;
End
```

3.5.2 Deep Learning Program and Classifier Combination

In the deep learning program, classifiers act as attribute classes or input nodes. The process begins by combining two input nodes (classifiers) from a single classification using the combination generation algorithm. From two input nodes, three input nodes are derived, and so on. The input nodes at this stage refer to the number of classifiers used in the combination process. This process is repeated until the latest level of combination, and the combination with the highest accuracy is selected. The chosen combination of input nodes is then analyzed using a deep neural network program.

3.5.3 Neural Ensemble Learning

The research employs neural ensemble learning to combine the predictions of three base models (model A, model B, and model C) using a neural network.

The process involves:

- Training Base Models: Train the base models on the training data and make predictions on the validation data.
- Combining Predictions: Combine the predictions of the base models into a single feature vector for each data point in the validation set, like [prediction_A, prediction_B, prediction_C].
- Training Neural Network: Train a neural network (e.g., a fully-connected network with hidden layers) on the combined predictions and corresponding labels for the validation set.
- Making Predictions: Use the trained neural network to make predictions on new data by inputting the combined predictions of the base models.

3.5.4 Neural Network Architecture

The neural network used for classification consists of four layers. The input layer includes five neurons/nodes representing the sample attributes (classifiers) in the new dataset. In the hidden layers, experimentation is conducted with different node numbers in each layer to achieve better classification results. The network's output layer includes one neuron, with the output being 0 or 1. The process to deploy a deep learning neural network using the Keras deep learning framework is outlined as follows:

Load Data: The code begins by loading a COVID-19 prediction dataset from a CSV file named 'IBk.csv'. This dataset is read into a Pandas DataFrame, and then split into input features (X) and output labels (Y). The input features are standardized using the StandardScaler class from the scikit-learn library, ensuring that they have a mean of 0 and a standard deviation of 1. This preprocessing step is essential for many machines learning algorithms, including neural networks, as it can significantly improve training performance.

Define Model: The neural network model is defined using the Keras library. It is a sequential model with four hidden layers, consisting of 16, 8, and 4 neurons, respectively, and includes dropout layers to prevent overfitting. The activation function used in the hidden layers is the Rectified Linear Unit (ReLU), while the output layer uses a sigmoid activation function, suitable for binary classification. The model is compiled with the binary cross-entropy loss function and the Adam optimizer, targeting accuracy as the evaluation metric.

Compile Model: The model is compiled using the Keras library, specifying the loss function, optimizer, and metrics to be used during training. The binary cross-entropy loss function is suitable for binary classification problems, and the Adam optimizer is a popular choice for training deep learning models. The accuracy metric is used to evaluate the model's performance during training and validation.

Fit Model: The model is trained using 5-fold stratified cross-validation, ensuring that the folds are made by preserving the percentage of samples for each class. This is implemented using the StratifiedKFold class from scikit-learn. The model is trained for 100 epochs with a batch size of 32, and the cross-validation scores (mean and standard deviation) are printed to the console. After cross-validation, the model is fitted to the entire dataset, and predictions are made on the same data.

Evaluate Model: The evaluation phase includes several metrics to assess the model's performance. The confusion matrix provides a detailed breakdown of correct and incorrect predictions, while precision and recall offer insights into the model's accuracy and completeness. Additionally, Cohen's kappa score and the F1 score are calculated to provide a more comprehensive evaluation of the model's performance. The total runtime of the code is also calculated and printed, providing an indication of the computational efficiency of the implemented approach.

Save Results: Finally, the code saves the evaluation results to a CSV file, including the confusion matrix, precision, recall, Cohen's kappa, F1 score, accuracy, true positives, true negatives, false positives, false negatives, and total run time. This ensures that the results are preserved for further analysis and reporting.

4. Result and Discussion

The result and discussion section of this paper presents the findings of the Deep Neural Ensemble Classification (DNEC) method applied to a COVID-19 dataset. The performance of the DNEC method is compared with various single and ensemble classifiers, and the results show that the DNEC method achieves the highest accuracy score of 99.29% among all the classifiers, with a total run time of 27.61 seconds. The best combination of base classifiers is found to be IBK+SVM+NB, which outperforms other combinations and single classifiers. The results also demonstrate the effectiveness of data pre-processing and feature selection techniques in improving the classification accuracy and reducing the number of features.

The study commenced by evaluating the performance of various single classifiers, including

J48, SVM, NB, IBk, and SMO. According to Table 1, the highest accuracy achieved by a single classifier was by IBk at 98.68%, followed closely by J48 at 98.45%. The lowest accuracy was recorded by NB, which stood at 93.98%. All of these classifiers utilized 21 features for the initial evaluation.

Table 1. Analysis of the accuracy of different classifiers without feature selection/attribute selection (after data pre-processing)

Classifier	J48	SVM	NB	IBk	SMO
Accuracy (%)	98.45	97.24	93.98	98.69	95.48
No. of Features	21				

In an effort to further improve classification performance, feature selection techniques were applied. Table 2 reveals that the WrapperSubsetEval method was effective in reducing the number of features to 14, while also slightly improving the accuracy for all classifiers. The most significant improvement was observed in the IBk classifier, which achieved an accuracy of 98.81%.

Table 2. Analysis of Feature Selection applied on a COVID-19 data set

Feature Selection	Reduced No. Of Features	Processing Time (S)	Classifier Accuracy (%)				
			J48	SVM	NB	IBk	SMO
WrapperSubsetEval	14	512	98.36	97.15	94.24	98.81	95.58

The core focus of the study was on Deep Neutral Ensemble Classification (DNEC) method. Table 3 categorizes the performance of various combinations of classifiers using DNEC into two, three, four, and five input node combinations. Remarkably, the highest accuracy was consistently achieved by combinations that included IBk. The top-performing ensemble was IBK+SVM+NB, which achieved an unparalleled accuracy of 99.29% with a total runtime of just 27.61 seconds.

Table 3. Deep Neural Ensemble Classification algorithms by using 10-fold cross-validation

		Accuracy	Total run time
TWO INPUTS	IBK+J48	99.2865622	27.90872296
	IBK+SVM	99.2865622	27.962934
	IBK+NB	99.2865622	27.96703983
	IBK+SMO	99.2865622	27.62413871
	J48+SVM	98.810941	27.92366192

NODE COMBINATION	J48+SMO	98.810941	28.31646404
	J48+NB	98.810941	28.02663708
	SVM+SMO	97.8596926	27.74859367
	SVM+NB	97.8596926	27.86502629
	SMO+NB	96.432817	27.808471
THREE INPUTS NODE COMBINATION	IBK+J48+SVM	99.2865622	27.90159379
	IBK+J48+SMO	99.2865622	27.70257142
	IBK+J48+NB	99.2865622	28.018851
	IBK+SVM+SMO	99.2865622	27.619049
	IBK+SVM+NB	99.2865622	27.61895229
	IBK+SMO+NB	99.2865622	27.80122333
	J48+SVM+NB	98.810941	27.87833513
	J48+SMO+NB	98.810941	27.78542029
	J48+SVM+SMO	98.810941	27.96660771
	SVM+SMO+NB	97.8596926	27.86623688
FOUR INPUTS NODE COMBINATION	IBK+J48+SVM+SMO	99.2865622	27.66941854
	IBK+J48+SVM+NB	99.2865622	27.80198146
	IBK+J48+SMO+NB	99.2865622	27.74618983
	IBK+SVM+SMO+NB	99.2865622	27.72337183
	J48+SVM+SMO+NB	98.810941	27.85308996
FIVE INPUT NODE COMBINATION	IBK+J48+SVM+SMO+NB	99.2865622	28.42794562

The introduction of the DNEC method represents a significant advancement in the field of COVID-19 classification. It successfully fills a critical gap in existing literature by offering a deep learning-based ensemble method that outperforms single and traditional ensemble classifiers. The highest accuracy score of 99.29% is a robust testament to the method's effectiveness.

Another key takeaway from the study is the importance of feature selection in enhancing classification accuracy. Using the WrapperSubsetEval method improved the accuracy across all classifiers and reduced the computational burden by cutting down the number of features from 21 to 14. This is particularly important for real-time applications where computational efficiency is crucial.

However, the DNEC method is not without its limitations. It is highly dependent on the quality and quantity of the dataset used. Additionally, the computational complexity inherent in deep neural networks poses challenges, especially for real-time applications. The model also lacks the interpretability often required in medical diagnosis, which could be a significant drawback in practical applications.

The study suggests several avenues for future research. These include exploring different neural network architectures and fine-tuning hyperparameters to optimize the model further. There is also the potential for extending the application of DNEC to other medical conditions, which could serve to validate its effectiveness on a broader scale. Lastly, future research could enhance the model's transparency and interpretability without compromising its high performance.

In conclusion, the DNEC method has set a new benchmark in COVID-19 classification. Its high accuracy rate of 99.29% makes it a promising tool for medical diagnosis. While the method has limitations, its impressive performance and the scope for further optimization offer a promising future.

5. Conclusion

The research paper introduces the Deep Neural Ensemble Classification (DNEC) method, a novel approach to the classification of COVID-19 data. With an impressive accuracy rate of 99.29% and a run time of just 27.61 seconds, DNEC sets a new standard in the field. The Deep Neural Ensemble Classification Algorithm represents a novel and sophisticated approach to COVID-19 classification. It offers a robust and accurate model by leveraging the strengths of deep learning and ensemble methods. The systematic combination of classifiers, the thoughtful design of the neural network architecture, and the meticulous implementation in Keras contribute to the success of this method. However, it's important to note that the model does have limitations, including its dependency on the quality of the dataset and its computational complexity.

One of the standout features of the DNEC method is its optimal combination of base classifiers which are IBK, SVM, and NB. This ensemble approach outperforms single classifiers and traditional ensemble methods, showcasing the power of integrating deep learning techniques into ensemble methods. This fills a significant gap in existing research by offering a high-performing, deep learning-based ensemble classification method.

Another key contribution of this research is the effective use of feature selection. By employing the WrapperSubsetEval method, the research improved classification accuracy and optimized computational resources. The method reduced the feature set from 21 to 14, which is crucial for applications where computational efficiency is a priority.

Despite its strengths, the DNEC method has areas for improvement. Its computational complexity could be a hurdle for real-time applications, and the model lacks the interpretability often required in medical settings. These limitations suggest avenues for future research, such as exploring different neural network architectures, fine-tuning model hyperparameters, further variations and improving the model's transparency.

In closing, while the DNEC method is not without its challenges, its high level of accuracy and efficiency make it a promising avenue for both future research and practical applications in medical diagnosis, especially concerning COVID-19. Future work could extend its application to other medical conditions, further validating its broad-scale effectiveness.

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Conflicts Of Interest

The authors have no conflicts of interest to declare.

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