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Healthcare Cloud Computing-Based Intelligent COVID-19 Detection System with Iot integration using deep learning

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Abstract

The rapidly intertwined technologies of AI, cloud computing, and IoT have brought about a paradigm shift in the healthcare space, with real-time detection of diseases and personalized treatment as one of the major outcomes. Methods available today are either inaccurate or very inefficient when it comes to processing real-time health data streams from IoT devices, not having fault detection mechanisms adequately, being overfitted, and largely incapable of securely managing large volumes of very heterogeneous and unstructured healthcare data. This study presents a cloud-based intelligent COVID-19 detection system that uses DenseNet201-HBO-DNFN to accomplish enhancement on anomaly detection, real-time processing, and predictive analytics in e-healthcare. The system incorporates wearable IoT devices, medical imaging, and deep learning models to process respiratory rates, oxygen saturation, body temperature, and chest X-rays (CXR) into a cloud-based intelligent detection system for COVID-19. Preprocessing techniques, including Histogram Equalization and Min-Max Normalization, ensure improved image quality and standardized input for the model. The DenseNet201 architecture is known for great gradient flow and feature reuse; hence it combines with Hybrid Bayesian Optimization (HBO) and Deep Neuro-Fuzzy Networks (DNFN) to improve diagnostic accuracy. Optimization is done using a parallel computer, distributed file storage, and NoSQL databases in order to perform analysis in real time on very large scales. The new model was trained and validated against the COVID-19 Chest X-ray and CheXpert datasets, achieving a stunning 98.37% accuracy, 98.70% precision, 97.53% recall, and 98.06% F1-score for the end-to-end evolved classifiers to excel. A continuous upward slope in training and validation accuracy graphs was noted to ensure learning effectiveness, whereas loss graphs prove reduced overfitting. Because of this, early disease diagnosis, fault detection, and efficiency prediction in healthcare have been improved - the proposed DenseNet201-HBO-DNFN with much faster interventions and much better real-time analyses improved the patient treatment outcome

Keywords: Artificial Intelligence (AI); Internet of Things (Iot); Cloud Computing; COVID-19 Detection; Densenet201; Hybrid Bayesian Optimization (HBO); Deep Neuro-Fuzzy Networks (DNFN); Anomaly Detection

1. Introduction

AI is disrupting the healthcare sector by making things better with patients, competent use of resources, and better overall healthcare systems. The Turkish National AI Strategy and AI Cognitive Empathy Scale will do wonders on the

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market performance and satisfaction of the patients.[1], [2], [3], [4], [5] By merging artificial intelligence and big data analytics with m-health systems of wearables and IoT devices, mobile technology will serve as a jump start in the advancement of healthcare into modernity. Predictive models are increasingly becoming the cornerstone to early disease detection and personalized treatment in which a cloud hosts huge-but-complex data so that they can be processed in a scalable and efficient way. [6], [7], [8], [9], [10] MARS, SoftMax Regression, and Histogram-Based Gradient Boosting are further potency-enhancing techniques adding to prediction accuracy on cloud-based frameworks. Traditional methods such as CRISP-ML, DeepAISE for early sepsis prediction, and interpretation tools like LIME and DeepLIFT are also at play in AI model interpretability and reliability.[11], [12], [13], [14], [15] AI and ML are already changing the geriatric space and bringing their disruptive touch in enabling predictive modeling for effectively managing chronic diseases, fall prevention, and individualized care within a preemptive healthcare framework.[16], [17], [18] This will ensure ready access to health care well in advance. The rapid pace of innovation in healthcare propelled by artificial intelligence, cloud computing, and consumer wearable IoT devices-the fusion of which can consistently complement each other to meet the demands for accurate and efficient diagnosis and management of disease-will rapidly solve the accurate and efficient demand on disease diagnosis and management.[19], [20], [21]

Cloud computing (CC), artificial intelligence (AI), and the Internet of Things (IoT) have made it possible for healthcare to experience a revolution in real-time data processing and precise disease diagnosis. [22] On another level, because of the explosive growth in data due to IoT systems worldwide, secure document clustering has become a necessity. Both MQC and SDC provide data security and efficiency. [23] Traditional models are somehow incapable of striking a balance between the processing efficiency and accuracy of these optimized solutions for real-time health data streaming from IoT devices. [24] Hence the combination of Affinity Propagation (AP) clustering and MQC encryption will ensure efficient organization while maintaining data security.[25] With growing concerns for data confidentiality in cloud-based healthcare, the need arises for the adoption of advanced encryption mechanisms to thwart constantly evolving cyber threats, including threats from quantum computing.[26]

2. Literature Review

Poovendran Alagarsundaram et al.[27] propose a Heterogeneous Network System (HNS) for privacy-preserving e-Healthcare Risk Prediction, which augments risk assessment and personalized healthcare using Health Big Data and Polygenic Score computation. Naresh Kumar et al. [28]decompose, denoise, compress, and extract features from ECG signals using DWT with HPF and LPF, thus making the real-time analysis feasible through IoT and cloud servers. The secure mobile healthcare framework with WBANs and multi-biometric key generation is facilitated through cloud computing for scalable data processing and EMR privacy. Mobile Health- A Secure Tech Deployed on Health Wireless Body Area Networks by Deevi et al.[29] The research by Grandhi S.H. et al.[30] enhances EEG frequency analysis through Versatile Inspiring Wavelet Transform (VIWT) and Adaptive Wavelet Transform (AWT), which are effective to determine brain activities in children, even in circumstances with disturbing levels of noise.

Basava et al.[31] have initiated the development of the AI-enabled Smart Comrade Robot which provides elderly care by merging AI and robotics as a means to assure everyday assistant tasks, health monitoring, and emergency response, which further ensues safety and lessens caregiver stress. Devarajan et al.[32] assessed AI models, including SVC, KNN, and Random Forest, with results by SVC proving to be the best among the three (0.8771), while they emphasized the need for interpretability of models for adoption in medicine. Panga et al. [33]have brought approaches such as ML and DL methods such as Decision Trees, CNNs, RNNs to health fraud detection. The Decision Tree Classifier achieved an accuracy rate of 99.9%, demonstrating how apparent-indicated models improve healthcare systems.

Gudivaka et al. [34] and other authors suggested the framework, this is an e-healthcare integrating IoT and fog computing to detect abnormality in health, behaviour, and that of physical posture and even in the environment with a mechanism for fault detection by weighted K-Means clustering model into the fog layer and a hybrid WKMC-DT approach for the early prediction of health severity in the cloud layer. The performance of the framework was established through the observation of 15 persons within a time frame of 30 days. Sitaraman et al.[35] focused on the data of healthcare systems of collection, processing and storage but also investigated how newer technologies such as distributed file storages, NoSQL databases and parallel computing created an avenue for real-time analysis and personalized health services. Sitaraman et al.[36] also stressed how AI, more specifically neural nets with accuracy of 92 percent, interlinked with Apache Spark and Hadoop would improve data management using health care data and allow timely intervention, while addressing the challenge of unstructured data and data privacy matters. Stresses the transformation possible through AI and Big Data in health care while outlining a need for further investigation.

2.1. Problem Statement

Early illness severity prediction and anomaly detection are made more difficult by the explosive rise of e-healthcare integrating IoT and fog computing. This study tackles the challenges of large-scale data management while improving accuracy through the use of a hybrid WKMC-DT technique and a weighted K means clustering model[34]. It guarantees effective real-time analysis and individualized healthcare services by utilizing decentralized storage of files, NoSQL databases, as well as parallel computing[35].

2.2. Objective

This research work proposes a COVID-19 intelligent detection system, which is cloud-borne and uses DenseNet201-HBO-DNFN technologies to derive improved anomaly detection and prediction analytics in e-healthcare. It augments the early health severity prediction as well as fault detection with IoT and fog computing. The model comprised DenseNet201 with the addition of Hybrid Bayesian Optimization (HBO) and Deep Neuro-Fuzzy Networks (DNFN), thus having high accuracy as well as high scalability. High-end data management techniques such as those based on distributed storage, NoSQL databases and parallel computing guarantee real-time analysis and personalized healthcare.

3. Proposed DenseNet 201-HBO-DNFN for Cloud Computing-Based Intelligent COVID-19 Detection System

The proposed cloud computing-based intelligent COVID-19 detection system utilizes the collaborative power of IoT-enabled medical sensors, cloud computing, and deep learning models, which further are optimized using advanced evolutionary algorithms, for increased accuracy and efficiency in COVID-19 detection. This system is structured on a multi-tier architecture, wherein wearable IoT devices and medical imaging tools acquire patient health data regarding respiratory rates, oxygen saturation, body temperature, and chest X-ray (CXR) or CT images. These data are transferred securely to the cloud infrastructure for further processing, and during preprocessing, these data will carry out image enhancement (CLAHE) and normalization to maintain standardized input quality for deep learning models.

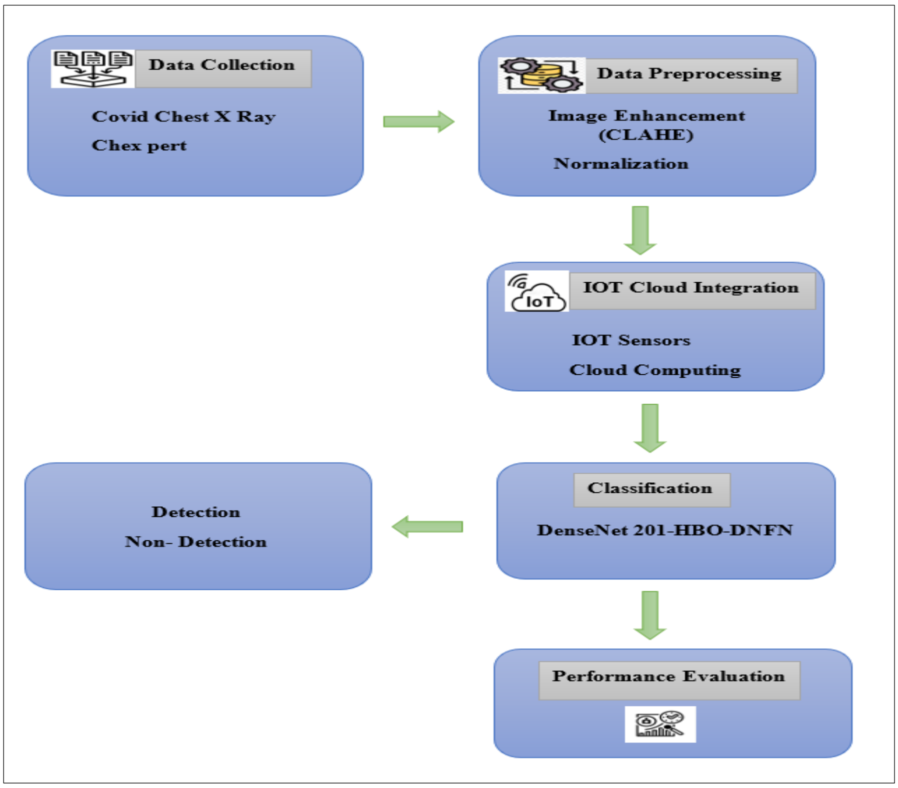


Figure 1 DenseNet 201 with Honey Badger Optimization-Based Deep Neuro Fuzzy Network (HBO-DNFN) Cloud Computing-Based Intelligent COVID-19 Detection System

3.1. Data Collection

The datasets used for the COVID-19 Detection System include the COVID-19 Chest-X Ray dataset and the CheXpert dataset. The first contains images that are labelled as positive for COVID-19, normal, or related to some other pneumonia infectious disease. These images were sourced from various health institutions and are applied to training and testing. On the belief that using data from the CheXpert dataset, which consists of chest X-ray images annotated for 14 disease categories, would enhance the accuracy of distinguishing those infected from other respiratory conditions associated with COVID-19.

3.2. Data Preprocessing

High-quality as well as consistent images are input into the model thanks to data preprocessing. To improve quality as well as standardize the data inputs for deep learning models, preparation includes image enhancement and normalization.

3.2.1. Image Enhancement

Image enhancement techniques like Histogram Equalization improve the contrast of images in a way that it becomes easy for the model to extract meaningful features from these images. The overall process of histogram equalization includes calculating the histogram of the input image, computing a cumulative distribution function (CDF), normalizing the CDF, and applying the new intensities based on the normalized CDF. This process usually results in a more equal distribution of pixel intensities along with increased contrast. The factor that separates this process from others is that it allows the detection of very small anomalies in medical images.

Equation for histogram equalization

$$h(r_k) = \text{ Number of pixels with intensity } r_k$$

$$CDF(r_k) = \sum_{i=0}^{k} h(r_i) \quad \ldots\ldots\ldots\ldots\ldots\ldots \text{(1)}$$

$$CDF_{\text{normalized}}(r_k) = \frac{CDF(r_k) - CDF_{min}}{N - CDF_{min}} \times (L - 1) \quad \ldots\ldots\ldots\ldots \text{(2)}$$

$$r'_k = CDF_{\text{normalized}}(r_k)$$

Additionally, Gaussian Smoothing or Anisotropic Diffusion is used for noise removal to enhance image quality and preserve edges.

3.2.2. Normalization

To enhance model convergence, normalization makes ensuring that every pixel value falls within a predetermined range, usually between 0 and 1. The pixel values are scaled to a standard range using the Min-Max Normalization approach. In this procedure, the least pixel value is subtracted, and the result is divided by a number of pixel values.

Equation for Min-Max normalization

$$I_{\text{normalized}}(x, y) = \frac{I(x,y) - I_{\min}}{I_{\max} - I_{\min}} \quad \ldots\ldots\ldots\ldots \text{(3)}$$

Where $I_{\min}$ and $I_{\max}$ represent the minimum and maximum pixel values, respectively.

3.3. IOT cloud Integration

The IoT in cloud health integrates different patient monitoring devices with the cloud platforms for centralized data collection, organization, and analysis. Using an IoT-enabled device or medical equipment, vital signs like heart rate, blood pressure, body temperature, and oxygen saturation are taken in real time and sent into the cloud storage for processing. Besides health monitoring data about patients, medical images such as X-rays and CT scans are also stored and processed in the cloud. The cloud-based infrastructure allows for scalable storage and immense computing power for real-time assessment and decision-making.

3.4. DenseNet 201 hybrid Honey Badger Optimization-Based Deep Neuro Fuzzy Network for COVID-19 Detection System

A deep learning architectural from the Dense Convolutional Networks family, DenseNet-201 is renowned for its improved gradient flow and feature reuse effectiveness. With its 201 layers, DenseNet-201 uses dense connections so that every layer can receive input from every layer before it. This specifically assists medical picture classification jobs by removing computational redundancy, boosting gradient flow, and improving feature extraction ability.

3.4.1. Equation for DenseNet

$$H_l = H_{l-1}, X_l \quad \text{.........} \quad (4)$$

Where H_l is the output of layer $l_t H_{l-1}$ is the output of the previous layer, and X_l is the input to the current layer, which includes all preceding layer outputs.

Honey badgers search, the honey badger optimizing (HBO) methodology is a metaheuristic optimization. HBO effectively strikes a balance between exploitation and exploration tactics to arrive at the best answers in challenging situations. In order to include uncertainty and resilient decision-making, the deep neuro-fuzzy network (DNFN), which blends fuzzy logic and deep learning models, uses HBO to fine-tune its parameters.

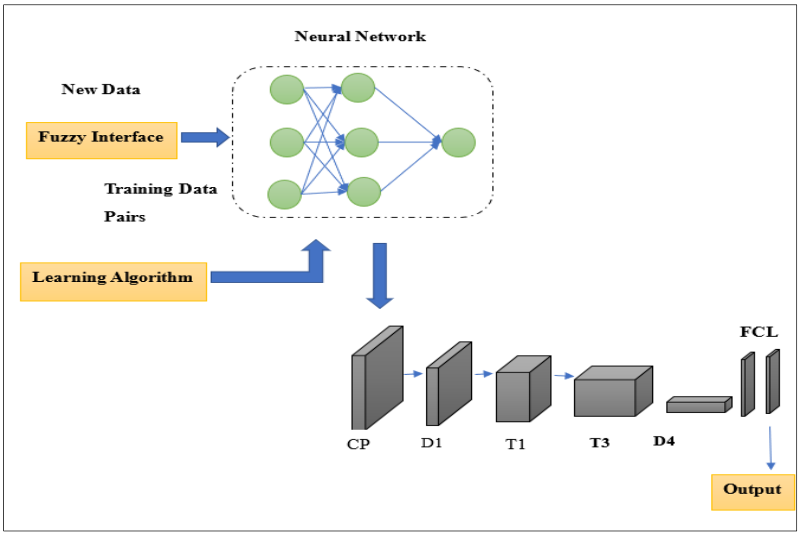


Figure 2 DenseNet 201 hybrid Honey Badger Optimization-Based Deep Neuro Fuzzy Network for COVID-19 Detection System

3.4.2. The HBO-DNFN equation is

$$X_t = X_{t-1} + \beta \cdot (X^* - X_{t-1}) + \gamma \cdot (X_{t-1} - X_{t-2}) \text{..........} \quad (5)$$

Where:
X_t is the current solution at iteration t,
X^* is the best-known solution,
β and γ are coefficients controlling exploration and exploitation, respectively.

4. Result and Discussion

With outstanding results of 98.37% accuracy, 98.70% precision, 97.53% recall, and 98.06% F1-score, the recently suggested DenseNet201-HBO-DNFN model for cloud-based COVID-19 detection has been effectively evaluated, guaranteeing diagnosis reliability. While the loss graphs demonstrate overfitting decrease, the accuracy of the validation and training graphs show consistent learning. IoT, fog computing, and improved deep learning work together to enhance real-time analysis and improve predictive healthcare efficiency.

4.1. Performance Analysis

In Figure 3, With observed values of accuracy = 98.37%, precision = 98.70%, recall = 97.54%, and F1-score = 98.06%, the graph displays the performance metrics of the COVID-19 detection model DenseNet201-HBO-DNFN. This demonstrates the model's ability to diagnose COVID-19 cases while lowering false positive and false negative cases. This model's high recall and precision make it a good choice for real-time diagnostics in medical settings

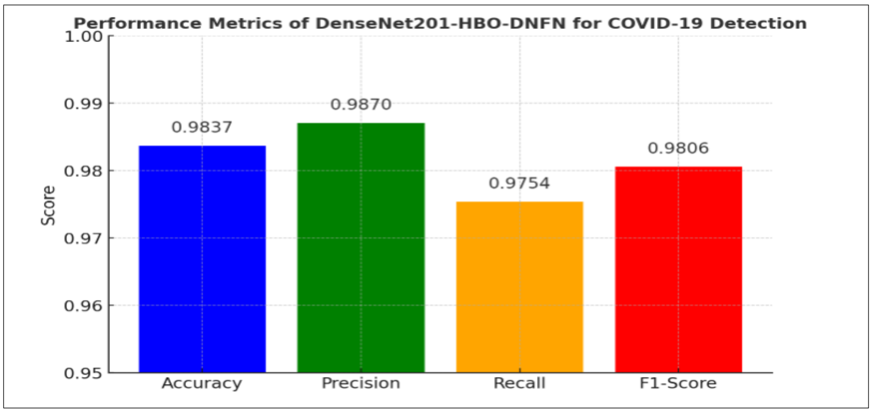
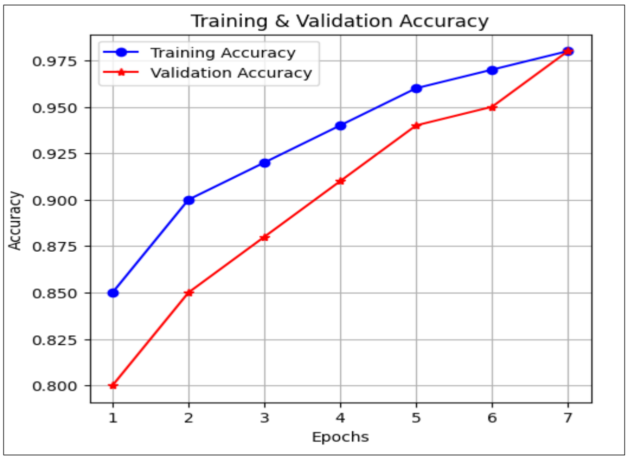
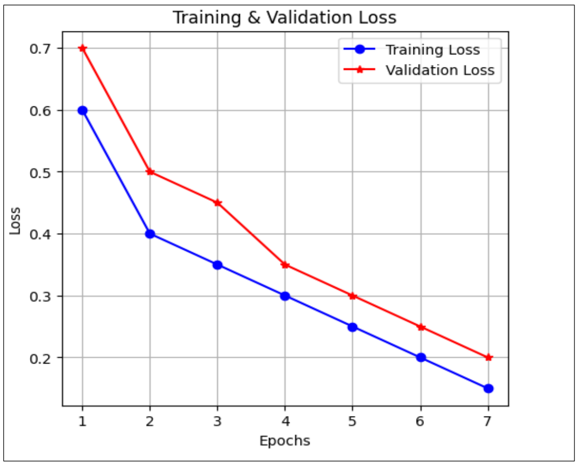


Figure 3 Performance Metrics

4.2. Training and Validation Accuracy and Loss





(a) (b)

Figure 4 (a) Training and Validation Accuracy, (b)Training and Validation Loss

Figure 4(a) shows a accuracy variations of the training and validation during seven epochs is presented for the DenseNet201-HBO-DNFN model. Both accuracies demonstrate an upward trend, indicating of effective learning. Following initial increases in training accuracy, validation accuracy catches up and eventually reaches about 97.5% in the most recent epoch, indicating a great deal of generalization and minimal overfitting. The model exhibits consistent and reliable performance in the context of COVID-19 detection in real-time healthcare applications.

In Figure 4 (b), The DenseNet201-HBO-DNFN model's training and validation failure trend were shown against the epochs. The model's successful learning and performance improvement are indicated by the decline in both losses. After initially being greater than the training loss, the validation loss gradually converges to reach minimal values in the final epoch. This suggests improved generalization and reduced overfitting, which will guarantee precise COVID-19 detection in the cloud-based healthcare system

5. Conclusion

DenseNet201-HBO-DNFN has a great level of high accuracy as well as robustness in detecting COVID-19 cases based on cloud computing, AI and IoT technologies for real-time self-healthcare applications. This model gives a diagnosis prediction with an accuracy of 98.37% to ensure that the disease prediction shows high reliability with very minimal overfitting. It passes training and validation performance tests with excellent generalization characteristics which render it ready for large-scale deployment. It was possible, through this investigation, to increase the efficiency of predictive healthcare in prompting timely and accurate diagnosis for improved patient outcomes.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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