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# A multi-model unified disease diagnosis framework for cyber healthcare using IoMT- cloud computing networks

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**Abstract**

The past several decades of research into machine learning have been of great assistance to humanity in the diagnosis of a variety of ailments using various forms of automated diagnostic procedures. Machine learning, combined with smart health devices, has improved health monitoring, timely diagnoses, and treatment. This paper introduces a unified disease diagnosis framework, integrating cloud computing, machine learning, and IoT. The framework has three layers: physical (collects patient data), fog (intermediate layer with a domain identification unit to determine input and diagnosis type), and transmission (cloud server with a disease detection unit). The performance evaluation shows the robustness and efficiency of the model as compared to state-of-art models.

***Subject Classification:*** *68Uxx.*

***Keywords:*** *Smart healthcare, Internet of Things, Cloud computing, Machine learning, Disease diagnosis.*

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## 1. Introduction

The Internet of Things (IoT) is a transformative technology, connecting computing resources with sensors to enhance efficiency [1]. It's pivotal in creating smart homes and cities. In healthcare, the Internet of Medical Things (IoMT) is addressing health disparities and enabling remote surveillance. Integrating cloud computing with IoMT ensures quick data processing. The growth of IoT and cloud technologies has spurred a need for frameworks offering patient-centric, high-quality, affordable smart healthcare[2]. Advances in machine learning and AI are making these frameworks even smarter, meeting the rising demand for real-time, efficient healthcare services [3]. Deep learning and AI are revolutionizing cognitive abilities and decision-making in healthcare [6]. With advancements in technology, stakeholders have access to innovative mobile devices and smart sensors. The healthcare industry is rapidly growing due to high demand , benefiting both patients and the sector financially. There's intense competition among providers to offer reliable and cost-effective services to smart city residents [7]. As a result, recent study has focused on how to effectively integrate cloud technologies and the Internet of Things (IoT)[8][9]. As a result, a significant number of academics have endeavored to include the idea of cognitive behavior in the process of intelligent IoT and developing smart frameworks. In the context of smart healthcare, the framework makes use of Internet of Things (IoT) sensors that are either attached to or located around a patient to gather data. A system like this one takes into account all of the health indicators and decides whether or not emergency medical assistance or specialist medical treatment is necessary. In addition to this, the framework ensures that all relevant smart healthcare stakeholders are kept up to date on patient status outcomes as well as monitoring results. Without cognitive capabilities, the idea of intelligent healthcare is hazy.

As a result, academics are currently devoting a large amount of effort to making progress in this area. Therefore, in this paper, a unified framework is designed to distinguish disease based on input type of disease as symptoms and diagnostic report. For this two novel units are introduced i.e. domain identification unit (DIU) and disease detection unit (DDU). The DIU unit integrated a symptom-disease relation matrix generated to differentiate among similar diseases. To distinguish among different medical images, the DIU unit integrated the YoloV5 model for object detection such as brain, lung, etc. For the classification of diseases, DDU unit has adopted a majority voting (MV) machine learning approach.

The entire paper is structured as follows: The related work of the cyber-physical system enabling methods in the healthcare industry is presented in Section 2. The materials and methods used for creating a uniform illness diagnosis model for smart healthcare is described in Section 3 of this study. The results and discussions of the provided unified model with a comparison to the state-of-the-art are presented in Section 4. The conclusion part is presented in Section 5, along with recommendations for future work.

## 2. Related Work

Cyber-physical systems incorporate advanced technologies such as artificial intelligence, big data analytics, and cloud computing, all of which are vital for modern healthcare and medical systems. The ultimate aim of contemporary healthcare is to deliver personalized, universally accessible, and patient-centric services [5][6]. To achieve this, intelligent medical systems have been developed, leveraging machine learning algorithms for diagnosis and treatment [7]. There are significant gaps in healthcare research models. Most are unimodal, concentrating exclusively on specific data like symptoms or medical imaging. Additionally, IoT-based healthcare data frequently face challenges such as misclassification, imbalance, and overfitting. Furthermore, while imaging techniques are being adopted, managing vast data volumes is a persistent hurdle. To address these gaps, a systematic meta-analysis was undertaken. Research articles were sourced from ACM, IEEE, Science Direct, Springer, among others, using keywords "smart healthcare" and "disease diagnosis". A bibliometric analysis is depicted in Figure 1.

There major contributions of researchers for disease diagnosis in the healthcare sector are discussed below based on architecture, mode, and

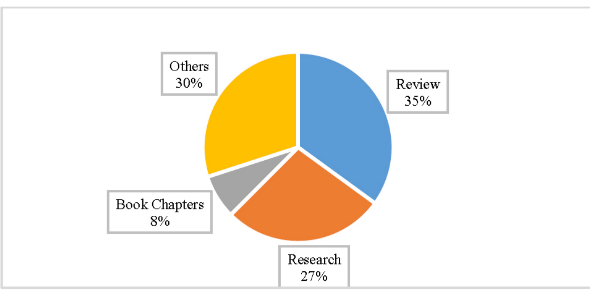


**Figure 1**

**Bibliometric Analysis for Disease Diagnosis in Smart Healthcare Research**

diagnosis approach. Various researchers have proposed models for disease diagnosis using IoT and machine learning techniques. Yin et al. [1] employed Fuzzy logic and GBDT to create a heart disease model, enhancing generalization and reducing overfitting through bagging, with a 90% accuracy. Alhussein et al. [2] introduced a fuzzy-Bi-LSTM model for heart disease, and Nancy et al. [5] applied a crow search algorithm with a cascaded LSTM network, achieving up to 97.26% accuracy for heart disease and diabetes. Despite their successes, these models had computational challenges and were limited to binary classification. Sekhar et al. [4] and Yuan et al. [3] furthered this work, introducing fine-tuned models like GoogLeNet and a hybrid CNN-LSTM for brain tumor detection. However, these models had computational demands and lacked comprehensive feature engineering. Haq et al. [6] introduced an ECG signal classification system using ResNet, addressing data imbalance with SMOTE, and attaining a 99% accuracy, but it didn't identify the specific disease type or severity.

## 3. Materials and Methods

The section outlines the materials, methods, system model, network architecture, and algorithms. The system operates in three layers:

- Physical Layer: Focuses on data collection, either from symptoms, diagnostic reports, or medical images.
- Fog Layer: Transmits collected data to the cloud.
- Application Layer: Analyzes data and predicts diseases using deep learning on a cloud server.

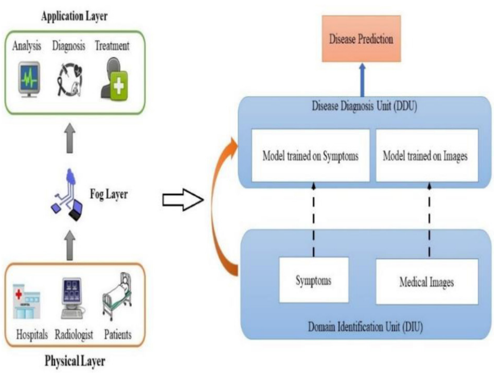


**Figure 2**

**Proposed Smart Healthcare Architecture**

The architecture consists of two main units: the domain identification unit (DIU) and the disease diagnosis unit (DDU), Figure 2. DIU, located in the fog layer, gathers data samples from the physical layer and forwards them to DDU. Unlike prior research [9][10], the physical layer in this design supports multiple disease diagnoses.

3.1 *Domain Identification Unit*

In the proposed Domain Identification Unit (DIU), two-level domain identification will be performed, as presented in Figure 3. In the first level, the type of input will be determined. If the input is of symptoms/ diagnostic report type, then in the second level, its input parameters will be verified with a disease dictionary and identify its type. Whereas if the input is image type (i.e., MRI/X-ray/CT-scans, etc.), then in the second level, its domain (organ) is identified either it is of the brain, lung, etc. The overall algorithm of the DIU is presented in algorithm 1.

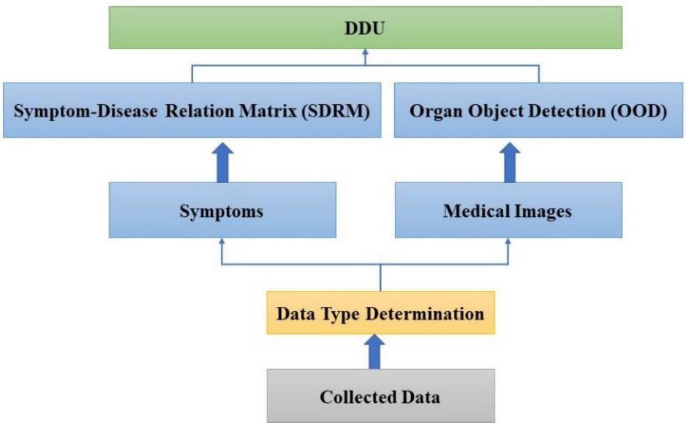


**Figure 3**
**Flowchart of DIU**

**Algorithm 1: Domain Identification Unit**

Input: Collected Sample Data $D_s$

Output: Data Type with Respective Features set $\{D_T, F_s\}$

1: Begin

2: For i=1:n *{n = number of patients or users}*

3: Identify $D_T \to \{I, S\}$ *{I= image, S = Symptoms}*

If $D_T \rightarrow S$
Generate $D_s \underset{sd_d}{\Rightarrow} SDRM$ *{ $sd_d$ symptom-disease dictionary}*
$F_s \leftarrow SDRM$
Else
Generate $D_s \underset{ODD}{\Rightarrow} O_t$ *{$O_t$ organ type}*
$F_s \leftarrow O_t$
End If
End for
Return
End

### 3.1.1 Symptom-Disease Relation Matrix

In this step, the Symptom-Disease Relation Matrix (SDRM) is generated by mapping the symptom-disease dictionary $sd_d$. Here, the set of symptoms is represented as $S = \{s_1, s_2, \ldots, s_p\}$ and a collection $C \subseteq 2^{\{s_1, s_2, \ldots, s_p\}}$ is monotonous for $\forall D$ of $D \in C$ and $C \subseteq S$. A symptom-disease structure $\{s_1, s_2, \ldots, s_p\}$ is a non-empty collection of set C. The collection in C is a set of verified symptoms for diseases. This symptom-disease structure is a Boolean structure.

### 3.1.2 Organ Object Detection

If the data type is identified as a medical image, then before sending data to DDU, the organ needs to be identified. This will make the diagnosis process easier. Suppose the organ is identified as the brain, then DDU will apply the model to identify the tumorous region or if the organ is identified as the lungs, then DDU will apply the lung infection detection model for that. Therefore, this step is most important for disease diagnosis through medical images. Training the YOLOv5 network allows us to determine the most appropriate structure for organ detection. The YOLOv5 detector operates in a single stage, as shown in Figure 4. Its architecture comprises three main components: the backbone, the neck, and the output instrument. The backbone is tasked with the initial feature extraction from the input image, utilizing multiple Convolutional Neural Networks (CNN) across four layers. The neck network merges feature maps from different layers to prevent information loss, using the Feature Pyramid Network (FPN) and the Pixel Aggregation Network (PAN). The FPN distributes semantic features, while the PAN transfers object localization features. Within the neck, three different feature fusion layers produce varying scales of new feature maps. The Special Pyramid Pooling (SPP) module enhances flexibility by employing diverse pooling kernel sizes. Lastly, compression plays a pivotal role in reducing the spatial footprint of the feature map, lowering computational complexity, and refining essential features.

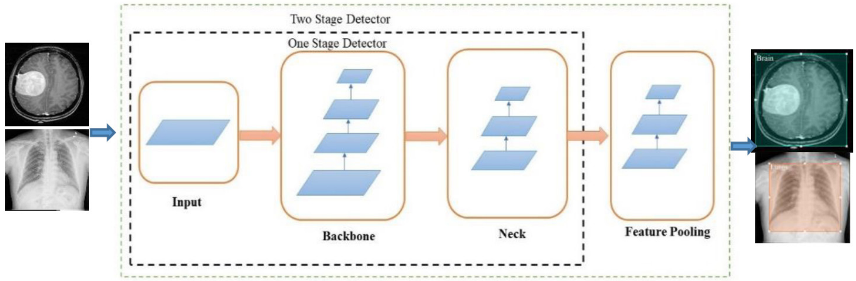


**Figure 4**

**The Architecture of the YOLOv5 Model**

3.2 *Disease Diagnosis Units (DDU)*

The outcome of the domain identification unit will be passed to the next unit, i.e., the disease diagnosis unit (DDU). Here, a machine learning model will be designed for the learning and identification of disease. Finally, if any disease is diagnosed in DDU, then its report will be displayed as disease prediction.

3.2.1 Disease Detection using Symptoms

The collected feature set of symptoms from DIU is used for the detection of disease. For that, this is divided into two steps: symptom-disease-associated features and classification. Let $S = \{s_1, s_2, \ldots, s_p\}$ be the set of symptoms respective for $D = \{d_1, d_2, \ldots, d_q\}$ diseases. The symptom-disease association is represented as $Y \in R^{n_s \times n_D}$. Here $Y_{pq}$ shows the similarity association among symptom $s_p$ and disease $d_q$. If it shows a positive correlation then its association is 1 otherwise 0. The study assesses symptom correlation similarity (SCS), suggesting that symptoms of common diseases exhibit similar patterns. A low-rank matrix then creates symptom-disease associations. Post this, the majority voting (MV) algorithm classifies diseases. Majority-based methods include voting (for classification tasks) and averaging (for regression tasks). Since disease diagnosis is a classification task, this paper employs the majority voting algorithm. Multiple base models train the data, and their outputs serve as MV algorithm input to predict diseases. To evaluate the overall error, the probability error of each base model is $1 - e_r$, where $e_r$ is the classification error. The binomial distribution function is applied to evaluate MV error, which is represented as:

$$\text{Prob }(X = \text{p}) = \binom{n}{p} e_r{}^p (1 - e_r)^{n-\text{p}} \tag{1}$$

Where p is the probability of valid predictions and $n$ is total predictions. Total probability is evaluated as:

$$Prob_{total} = \sum_{\text{p}>\frac{n}{2}}^{n} \binom{n}{p} e_r{}^p (1 - e_r)^{n-\text{p}} \tag{2}$$

By using a majority voting strategy, better accuracy as compared to the simple classifier. The classifiers used for designing the MV algorithm are as:

Support Vector Machines (SVM): A support vector machine (SVM) is a supervised learning model used for classification and regression. It works by determining the best hyperplane that categorizes data into two groups. Key concepts include data points, the hyperplane, and the margin. The closest data points to the hyperplane are support vectors, which help identify the optimal separation line. The margin represents the gap between these data points from different classes. While SVMs are linear classifiers like perceptrons and logistic regressions, they excel by maximizing the separation between the nearest training points and the decision boundary. To determine the decision boundary w, maximization of the margin is necessary and is evaluated as:

$$\sum_{i=1}^{n} w_i d_i^+ \geq +1 \tag{3}$$

$$\sum_{i=1}^{n} w_i d_i^- \geq -1 \tag{4}$$

Here, a positive and negative feature vector is represented as $d^+$ and $d^-$. The margin is represented as $\underset{w}{\rightarrow}$, where the decision boundary is represented as $w$.

Random Forests Classifier: This algorithm is a supervised machine learning method used for classification and regression. It builds Decision Trees (DT) from data samples, predicts using each tree, and chooses the most common outcome. The process starts with a root node containing all labeled data, then selects a feature and calculates a threshold. The data is split based on this threshold. If the splits are too small, they become leaf nodes; otherwise, they are further divided. This process continues until a specified depth is reached. The random subset is regenerated as:

$$round\sqrt{D} = round(log_2 x) \tag{5}$$

where x represents the characteristics, and "round" simplifies the number without changing its meaning.

**Extreme Gradient Boosting:** Collective machine learning algorithms like gradient boosting can be used to address difficulties with classification and regression modeling. Ensembles are built using decision tree models. Trees are simultaneously inserted into the array and matched to repair the misclassification in forecasting that was induced by previous models. Identical to how a neural network works, the loss gradient is minimized during the fitting process of a gradient-boosting model. Gradient-based methods are used to fit simulations, with the loss function being a user-selectable one that can be differentiated. Overfitting is a problem with the GBDT algorithm, hence the XGBoost method adds normalization parameters to the original GBDT algorithm.

### 3.2.2 Disease Detection using Medical Images

Medical image disease detection includes a key step toward enhancing disease treatment planning, monitoring, and clinical trials. Disease retrieval includes the detection of diseases such as brain tumors, lung infections, etc. But medical images can be acquired using a variety of protocols and typically have low contrast and inhomogeneous appearances. Figure 5 illustrates the research technique, which is comprised of four fundamental components: image pre-processing, data augmentation, feature extraction, and detection. Algorithm 2 illustrates the working of disease detection using medical images.

**Algorithm 2: Medical Image DDU**

Input : Training Data $T_{X,Y}$, Testing Data $Ts_{\hat{X}m}$, Classifiers $C_i\{i = 1, 2, ..., n\}$

Output: Prediction $\hat{Y}$

1. For i=1: $I_i$ $\{I_i$ is the input medical images $\}$

2. Normalize, $\hat{I}(x,y)=\frac{I(x,y)-Min_I}{Max_I-Min_I}$ Where, $Min_I$ = minimum intensity, $Max_I$ = maximum intensity
3. Calculate weight matrix, $W=\hat{I}_t^{\mu}$ Where, $\mu$ = enhancement degree controller
4. $\hat{I}_t=\max(\hat{I}_c(x,y)c\in\{R,G,B\})$
5. $O_i(x,y)=\hat{I}(x,y)*W$ $\{O_i$ is the pre-processed images$\}$
6. End
7. For i=1: $I_i$ do
8. $FV_{i_{deep}}\xleftarrow{\text{Transfer Learning}}O_i$ $\{FV_{i_{deep}}$ is deep feature vector$\}$
9. $RFV_{i_{deep}}\xleftarrow{PCA}FV_{i_{deep}}$

   $\{RFV_{i_{deep}}$ is reduced dimention feature vector$\}$
10. $P_i\xleftarrow{C_i}RFV_{i_{deep}}$
11. End
12. $\hat{Y}\xleftarrow{vote}p_i$
13. Return $\hat{Y}$
14. End

## 4. Results and Discussions

In this section, we have presented the results and discussions for presented unified multi-modal disease diagnosis smart healthcare model. The Google Colab Tesla P100-PCIE GPU is used to implement the specified model. The suggested model is implemented using a backend that combines Keras and Tensorflow. Below is section 4.1 we have presented the result analysis for symptom-based DDU. Section 4.2 presents the result analysis on medical image-based DDU. For performance evaluation, accuracy, precision, Recall, and F1_score are evaluated. Apart from this time complexity was also observed in the result analysis. These parameters are discussed below:

$$Accuracy=\frac{(TP+TN)}{(TP+TN+FP+FN)} \tag{6}$$

$$Precision=\frac{(TP)}{(TP+FP)} \tag{7}$$

$$Recall = \frac{(TP)}{(TP+FN)} \tag{8}$$

$$F1\_score = \frac{(2*Precision*Recall)}{(Precision+Recall)} \tag{9}$$

4.1 *Dataset Used*

DDU's result analysis based on symptoms uses data from the "National Health Portal of India" [19], managed by "The Centre for Health Informatics". The dataset comprises 261 diseases and over 500 symptoms. After preprocessing to eliminate duplicates, it contains approximately 8000 entries and around 450 unique symptoms. For DDU analysis based on medical images, datasets related to brain tumors and lung infections are used. The sources include brain tumor MRI datasets [12][13], the Alzheimer's Disease Neuroimaging Initiative (ADNI) [14], and a lung infection x-ray dataset [15].

4.2 *Symptom-based DDU*

Table 1 presents the result analysis for various DDU models based on disease symptoms, including models like naïve Bayes (NB), random forest (RF), and others. Figure 5 displays the execution times for each model, with MV taking the longest at ~32s due to its strategy of converging based on multiple classifiers' predictions. This longer execution time for MV is a limitation, suggesting potential future research areas.

**Table 1**

**Performance of Classifiers for Symptom-based DDU**

| Models | Accuracy | Precision | Recall | F1_score |
|---|---|---|---|---|
| NB | 85 | 90 | 85 | 85 |
| RF | 91 | **98** | 91 | 94 |
| K-NN | 91 | 95 | 91 | 93 |
| LR | 90 | 97 | 90 | 93 |
| SVM | 91 | 96 | 91 | 93 |
| DT | 87 | 93 | 87 | 88 |
| MLP | 89 | **98** | 89 | 92 |
| MV | **96** | 95 | **96** | **95** |

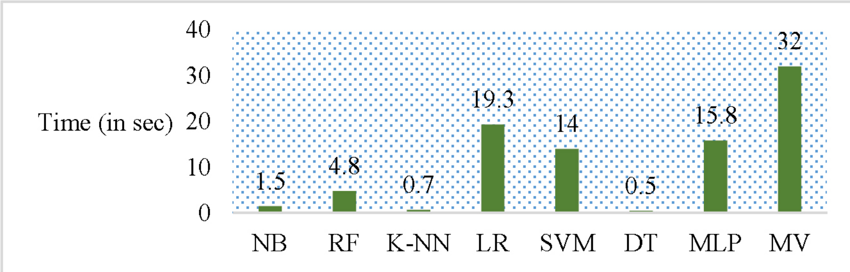


**Figure 5**

**Training Time of Symptom-based DDU**

4.3 *Medical Image based DDU*

This section performs result analysis on performance parameters as discussed above. Table 2 compares the MV-DenseNet Model with various state-of-the-art techniques for diagnosing brain tumors, Alzheimer's disease, and lung infections. Transfer learning, especially with models like VGG16, ResNet50, and InceptionV3 [16], is popular in medical image analysis. Among them, InceptionV3 has the highest accuracy at 89%. Other models like AlexNet and GoogleNet are introduced in [17]. A hybrid

**Table 2**

**Comparative State-of-Art Models**

| Models | Modularity | Dataset | Accuracy |
|---|---|---|---|
| VGG16 [16] | Uni-modal | Lungs | 84% |
| ResNet-50 [16] | Uni-modal | Lungs | 86% |
| InceptionV3 [16] | Uni-modal | Lungs | 89% |
| AlexNet [17] | Uni-modal | Lungs | 83% |
| GoogleNet [17] | Uni-modal | Lungs | 80.5% |
| CNN+LSTM [18] | Uni-modal | Lungs | 92% |
| CNN[12] | Uni-modal | Brain Tumor | 97.92% |
| GoogleNet[19] | Uni-modal | Brain Tumor | 97.1% |
| CapsNet [20] | Uni-modal | Brain Tumor | 90.89% |
| MLP [21] | Uni-modal | Alzheimer | 83.4% |
| DenseNet [22] | Uni-modal | Alzheimer | 89.54% |
| AttentionCNN [23] | Uni-modal | Alzheimer | 92.4% |
| MV-DenseNet | Multi-modal | Lungs, Brain Tumors, Alzheimer | 98% |

model (CNN+LSTM) [18] achieves 92% accuracy but is specific to lung infections. For brain tumors, models include CNN[20] (98% accuracy), GoogleNet[19], and CapsNet[20]. Alzheimer's disease detection comparisons involve MLP [21] with 83.4% accuracy, DenseNet [22] at 89.54%, and AttentionCNN [23] at 92.4%. Notably, existing models focus on individual diseases, while the proposed multi-modal model detects multiple diseases with a top accuracy of 98%. This unified approach supports comprehensive disease diagnosis, enhancing treatment processes.

## 5. Conclusion

Deep learning enhances the effectiveness of Healthcare IoT solutions, elevating health monitoring, diagnosis, and data collection standards. This paper introduces a unified model for multi-disease diagnosis aiming to create a comprehensive diagnostic framework. This system integrates cloud computing, machine learning, and IoT in a three-stage design: the physical layer, fog layer, and transmission layer. Disease identification is handled by the domain identification unit (DIU) and disease detection unit (DDU). Results indicate improvements over previous methods. The proposed framework, powered by deep learning, aims to simplify diagnosis challenges, with future plans to evolve it into a treatment recommendation system.

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