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# Cloud-Driven Predictive Healthcare System using CNN, HierbaNetV1, and LSTM for Chest X-ray and Patient Data Analysis

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***Abstract***

*Early and accurate diagnostic procedures are, therefore, essential in modern medicine dealing with thoracic disorders, where late diagnosis could bear a fatal consequence. In this paper, a cloud-integrated predictive healthcare system based on deep-learning methods is proposed to classify chest X-rays with sequential patient metadata. The presented model integrates a Convolutional Neural Network (CNN) for extracting spatial features, HierbaNetV1 for learning deep representation, and Long Short-Term Memory (LSTM) to capture temporal patterns from patient health histories. Experiments on the NIH Chest X-ray 14 database containing a total of 112,120 images belonging to 14 classes of diseases were performed. The said system achieved an accuracy of 99.64%, a precision of 99.75%, a recall of 99.51%, and F1 score of 99.63%, thereby outclassing the traditional approaches. Also, an AUC-ROC rating of 0.9975 and Average Precision of 0.9978 further confirm the astounding discriminatory performance of the model. The integrated imaging and temporal data residing on a cloud platform thus allows for a scalable real-time prediction and decision support for diseases, one of the suitable solutions for the intelligent healthcare environment.*

***Keywords:*** *Cloud-based healthcare, CNN, HierbaNetV1, LSTM, Chest X-ray, Disease Prediction, Medical Imaging, Sequential Data, AUC-ROC, Predictive Analytics.*

## 1. Introduction

The entire healthcare domain has been reshaped by cloud computing and advanced ML algorithms for the complex analysis and efficient scaling of medical data [1]. Chest radiography contributes to lung disease diagnosis with a huge volume of data that requires a sophisticated processing approach [2]. Manual interpretation is a primary characteristic of these traditional diagnostic methods, which forfeit time and lack uniformity amongst radiologists [3]. The advent of deep learning models such as LSTM networks and CNNs has greatly aided the automation process, thus enhancing their diagnostic accuracy [4]. This, however, poses greater challenges and requires even much more complex frameworks that will handle the integration of diverse patient data and zoning of interest in different scales of medical images [5]. Healthcare systems worldwide are increasingly adopting advanced technologies to improve disease diagnosis and patient care [6].

Medical imaging, especially chest X-rays, plays a vital role in detecting respiratory conditions such as pneumonia, tuberculosis, and COVID-19 [7]. With the rapid growth of medical data, traditional diagnostic methods are often time-consuming and prone to human error [8]. Leveraging artificial intelligence (AI) techniques, such as deep learning, can enhance the accuracy and efficiency of healthcare diagnostics [9]. Convolutional neural networks (CNNs) have shown great promise in analysing medical images by learning intricate patterns [10]. Additionally, cloud computing provides scalable storage and processing power, enabling the integration of large datasets and real-time analysis [11].

This paper proposes a cloud-based predictive healthcare framework regarding the multidimensional analysis of patient data-inclusive cases and chest X-ray imaging directly from CNN, HierbaNetV1 and LSTM networks, such enormous data sets are amenable to cloud processing power for acute real-time diagnosis and personalised patient management [12]. HierbaNetV1 so permits the handling of regions of interest from different granularity scales that favour extraction of those features that easily get deranged by the inclusion of such variable

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parameters—a recurring troublesome issue in medical imaging [13]. LSTMs can also handle sequential patient data analysis and make disease progression predictions over time [14]. This holistic approach will somehow improve patient outcomes and diagnostic specificity [15]. The increasing prevalence of respiratory diseases is driven by factors such as environmental pollution, lifestyle changes, and global pandemics [16]. Poor air quality and exposure to harmful substances contribute significantly to lung diseases [17]. Additionally, aging populations and sedentary habits exacerbate the risk of chronic respiratory conditions [18]. The surge in patient data, including medical images and clinical records, demands sophisticated tools to manage and interpret this information effectively [19]. Furthermore, limitations in healthcare infrastructure, especially in remote areas, create challenges in timely diagnosis and treatment [20]. This underscores the need for automated, accurate, and accessible diagnostic systems that can support healthcare professionals [21].

Despite advancements, several challenges hinder effective utilization of AI in healthcare [22]. Variability in image quality, lack of standardized datasets, and imbalance in labeled data affect model performance [23]. Many existing systems struggle with integrating diverse data types, such as combining imaging data with patient clinical information [24]. Privacy and security concerns around sensitive health data also pose significant barriers [25].

To address these challenges, the proposed cloud-driven predictive healthcare system combines CNN, HierbaNetV1, and LSTM architectures to enhance the analysis of chest X-rays alongside patient data. CNNs efficiently extract spatial features from images, while HierbaNetV1a specialized neural network improves hierarchical feature learning. LSTM networks handle temporal and sequential patient data, capturing vital trends over time. Utilizing cloud infrastructure ensures scalable computation, secure data storage, and facilitates remote access. This integrated approach enhances diagnostic accuracy, supports real-time predictions, and offers explainable insights to clinicians. Ultimately, it fosters a robust and accessible healthcare framework capable of improving patient outcomes globally.

### 1.1 Research Objectives

- Apply CNNs to process chest X-ray images to detect diseases, with HierbaNetV1 augmenting feature extraction from areas of interest across scales.
- Apply LSTM networks to process sequential patient data, modelling temporal relationships to forecast disease progression and outcomes.
- Build a cloud-deployed predictive healthcare platform that unifies CNNs, LSTMs, and HierbaNetV1, deploying it for real-time, scalable prediction and adaptive learning.

## 2. Literature Survey

Traditional evaluation methods of chest X-ray images rely highly on the subjective human assessment of the radiologists' very often inconsistent interpretations [26]. To aid interpretation, early computer-aided diagnostic systems used manually designed features and conventional machine learning techniques [27]. Traditional methods of evaluating chest X-ray pictures mostly depend on the subjective and sometimes inconsistent manual interpretation of radiologists themselves [28]. Deep learning has greatly impacted the advancement of medical image analysis, with convolutional neural networks significantly improving diagnostic accuracy by automatically learning hierarchical features from medical images [29]. For capturing temporal correlations of consecutive patient data, LSTM networks have been able to predict the disease onset [30]. Thus, the integration of these models with the cloud allows the processing of clinical datasets into big data quite effectively [31]. Traditional evaluation of chest X-ray images has long depended on the subjective judgment of radiologists, often leading to inconsistent interpretations [32]. Early computer-aided diagnostic (CAD) systems attempted to assist this process using manually crafted features combined with conventional machine learning methods, but these approaches had limitations in handling the complexity of medical images [33]. The emergence of deep learning, particularly convolutional neural networks (CNNs), has revolutionized medical image analysis by automatically extracting hierarchical features, significantly improving diagnostic accuracy [34].
Additionally, Long Short-Term Memory (LSTM) networks have proven effective in capturing temporal patterns from sequential patient data, enabling better disease progression predictions [35]. Integrating these deep learning models with cloud computing infrastructure further enhances the capacity to process and analyze large-scale clinical datasets efficiently, paving the way for more accurate and scalable healthcare solutions [36]. The recent trend in multimodal medical data interpretation has been to use CNNs along with LSTMs [37]. An example is an ensemble CNN-LSTM model developed to predict the functional recovery of stroke patients from combined MRI and clinical data, outperforming traditional methods in prediction accuracy [38]. However, challenges remain in effectively merging different data sources and segmenting regions of interest (ROIs) of varying sizes in medical images [39]. Contemporary models have not fully tackled the varying dimensions of processing ROIs and multimodal patient data integration [40]. Many current systems neither offer efficient nor scalable solutions for handling large datasets, highlighting the importance of cloud-centric architectures [41]. Overcoming these barriers will lead to more accurate and predictive healthcare systems [42]. Despite numerous advancements, variability in image quality, data heterogeneity, and lack of standardized datasets continue

to affect model performance [43]. Privacy and security concerns around sensitive health data pose additional barriers to widespread AI adoption in healthcare [44]. Computational resource demands for training deep learning models limit deployment in smaller healthcare facilities [45].

Furthermore, the interpretability of AI predictions remains critical, as clinicians require transparent and explainable outputs to trust and act on model results [46]. Multimodal medical data complexity often surpasses the capabilities of existing diagnostic systems to aggregate or process effectively [47]. Standard CNN architectures may fail to extract important features from differently sized ROIs, leading to information loss [48]. Many models overlook longitudinal patient data, making it difficult to predict disease evolution accurately [49]. Although big data discussions are common, scaling and efficient data processing remain challenging without cloud support [50]. Cloud computing offers scalable storage and processing power essential for managing large clinical datasets [51]. Integrating advanced neural networks with cloud platforms can improve diagnostic efficacy and real-time decision-making [52]. The hierarchical feature extraction capabilities of networks like HierbaNetV1 improve handling of multi-scale ROIs in medical images [53]. LSTM networks facilitate temporal analysis of patient data, enabling disease progression predictions [54]. Combining these strengths in a cloud-driven framework enhances personalized patient management and outcome prediction [55].

## 3. Problem Statement

Integrating and interpreting different forms of medical data such as images and sequential patient histories is a major challenge in predictive healthcare [56]. Conventional models have faced limitations with representing complex patterns in multiple-sized interest areas within medical images [57], and thus, their diagnostic performance is less than satisfactory [58]. When analysis of patient data does not include time-course modelling, the ability to accurately predict the course of a disease is severely curtailed [59]. For the purposes of concurrent integration and analysis of multimodal medical data, there is an urgent requirement for a new paradigm that integrates the latest neural net models CNNs, HierbaNetV1 and LSTM network swith cloud computing capabilities [60]. The new paradigm will, therefore, enable real-time processing of data for diagnostic precision and individualized treatment of patients [61]

## 4. Methodology

Secure upload of patient record data and chest X-ray images goes into a scalable and confidential cloud platform. The preprocessing stage involves separate image normalization and sequential patient data formatting processes for feature extraction. While CNN derives spatial features from the images, LSTM will extract the temporal dependencies presented in patient records. The modal fusion is then implemented using a layer and is then handled by HierbaNetV1 that has a tailored architecture for high disease prediction with result presentation in a cloud-based dashboard depicted in Figure 1.

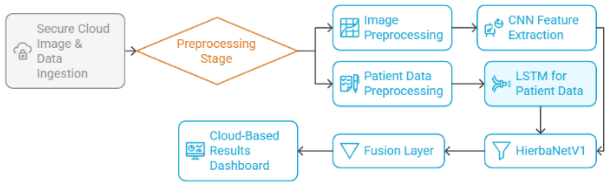


**Figure 1:** Architecture Diagram

### *4.1 Data Acquisition and Preprocessing*

The Chest X-ray images are normalized to channel-wise adjust pixel intensities and then resized for uniform input sizes across the network. Mild augmentations such as rotation and zoom are used to enhance model generalization and insensitivity to real-world image variability in medical imaging.

Let $\mathcal{X}_{img} \in R^{H\times W\times C}$ be the original image tensor.

- ***Normalization:***

$$\mathcal{X}_{norm}^{(i,j,c)} = \frac{\mathcal{X}_{img}^{(i,j,c)} - \mu_c}{\sigma_c} \quad (1)$$

where $\mu_c, \sigma_c$ are channel-wise mean and standard deviation.

- ***Resizing:***

$$\mathcal{X}_{resized} = \text{Resize}(\mathcal{X}_{norm}, 224\times 224) \quad (2)$$

- ***Augmentation (Rotation & Zoom):***

$$\mathcal{X}_{aug} = \text{Augment}(\mathcal{X}_{resized}; \theta, z), \quad \theta \in [-10°, 10°], \quad z \in [0.9, 1.1] \quad (3)$$

### *4.2 Patient Record Preprocessing*

Patient data are cleaned and formatted with missing vitals imputed with mean or forward imputation. The data features are normalized and augmented with timestamp embeddings to capture the temporal patterns in clinical data, making the sequence data format suitable for LSTM-based learning.

Let $\mathcal{D}_{pat} = \{\boldsymbol{v}_t\}_{t=1}^{T}$, where $\boldsymbol{v}_t \in R^n$ is the vector of patient vitals at time $t$.

- Missing Value Imputation (Mean/Forward Fill):

$$\mathbf{v}_t^{(j)} = \begin{cases} \mathbf{v}_t^{(j)} & \text{if present} \\ \frac{1}{T}\sum_{k=1}^{T} \mathbf{v}_k^{(j)} & \text{if missing} \end{cases} \quad (4)$$

- Normalization of Features:

$$\widetilde{\boldsymbol{v}_t^{(j)}} = \frac{v_t^{(j)} - \mu_j}{\max(v^{(j)}) - \min(v^{(j)})} \quad (5)$$

- Timestamp Embedding:

$$\boldsymbol{t_t} = \text{UNIX}(T_t), \quad \boldsymbol{v_t} = [\widetilde{\boldsymbol{v_t}}, \boldsymbol{t_t}] \tag{6}$$

4.2.1 Secure Cloud Storage

Pre-processed image and patient information are safely uploaded and stored on a cloud platform that is private. Encryption of data, API security, and controlled access features comply with healthcare privacy standards such as HIPAA to protect sensitive medical images and records from unauthorized viewing.

All pre-processed data $\{\mathcal{X}_{aug}, \mathcal{D}_{pat}\}$ are securely stored using:

- Encrypted REST APIs
- Access Control Lists (ACLs)
- Cloud Bucket Storage Policies

*4.3 CNN-Based Feature Extraction*

CNN automatically learn and extract important features from input images through multiple layers of convolution and pooling. These layers capture spatial hierarchies, detecting edges, textures, shapes, and complex patterns. Feature extraction by CNNs eliminates the need for manual feature engineering, improving accuracy and efficiency. The extracted features serve as rich representations for tasks like classification or segmentation. This makes CNNs highly effective in medical image analysis, such as detecting abnormalities in chest X-rays.

4.3.1 Lightweight CNN Encoder

A light CNN like MobileNet or EfficientNet is employed for obtaining high-level spatial features of processed chest X-rays. They depict diagnostic patterns like lung opacity or irregular areas that are fundamental visual cues to disease prediction.

Let $\Phi_{\text{cnn}}$ denote the CNN:

$$\boldsymbol{f_{cnn}} = \Phi_{\text{cnn}}(\mathcal{X}_{aug}) \in R^{d_1} \tag{7}$$

Where:

- $\boldsymbol{f_{cnn}}$ is the image feature vector.
- $d_1$: dimensionality of flattened feature map after global average pooling.

*4.4 HierbaNetV1 for Advanced Feature Extraction Multi-Kernel Feature Encoding*

HierbaNetV1 improves feature extraction of images with the help of multiple convolution kernels of different sizes. The architecture extracts multi-scale information from various parts of the chest X-ray such that the system can detect lesions or abnormalities of different sizes and locations.

Let $\Phi_k$ be convolution layers with varying kernel sizes $k \in \{3,5,7\}$:

$$\boldsymbol{f_k} = \Phi_k(\boldsymbol{f_{cnn}}) \quad \Rightarrow \quad \boldsymbol{f_{multi}} = \text{Concat}(\boldsymbol{f_3}, \boldsymbol{f_5}, \boldsymbol{f_7}) \tag{8}$$

4.1.1 Adaptive Attention Pooling

HierbaNetV1 has a built-in attention pooling scheme, which weights distinct areas of the extracted features with different weights. HierbaNetV1 dynamically focuses on those areas that contain more informative cues, which improves the model to detect subtle pathological patterns in X-ray images more effectively. HierbaNetV1 applies a weighted attention function $\alpha_i$:

$$\boldsymbol{f_{hierba}} = \sum_{i=1}^{m} \alpha_i \cdot \boldsymbol{f_{multi}^{(i)}}, \quad \alpha_i = \frac{e^{w^\top f_{multi}^{(i)}}}{\sum_{j=1}^{m} e^{w^\top f_{multi}^{(j)}}} \tag{9}$$

Were, $\boldsymbol{w}$ is learnable attention weight vector and $m$: number of feature segments.

*4.5 LSTM for Sequential Patient Data Modelling*

4.5.1 LSTM Cell Computation

LSTM networks process sequential patient data to learn temporal relationships. The LSTM gating mechanism allows it to learn long-term patterns such as deteriorating vitals or recurrent symptoms which are critical for making accurate predictions of disease progression. For time-series data $\boldsymbol{v_t} \in R^n$, define LSTM recurrence:

$$\mathrm{i}_t = \sigma(\mathrm{W}_i \mathrm{v}_t + \mathrm{U}_i \mathrm{h}_{t-1} + \mathrm{b}_i) \tag{10}$$
$$\mathrm{f}_t = \sigma(\mathrm{W}_f \mathrm{v}_t + \mathrm{U}_f \mathrm{h}_{t-1} + \mathrm{b}_f) \tag{11}$$
$$\mathrm{o}_t = \sigma(\mathrm{W}_o \mathrm{v}_t + \mathrm{U}_o \mathrm{h}_{t-1} + \mathrm{b}_o) \tag{12}$$
$$\mathrm{c}_t = \mathrm{f}_t \odot \mathrm{c}_{t-1} + \mathrm{i}_t \odot \tanh(\mathrm{W}_c \mathrm{v}_t + \mathrm{U}_c \mathrm{h}_{t-1} + \mathrm{b}_c) \tag{13}$$
$$\mathrm{h}_t = \mathrm{o}_t \odot \tanh(\mathrm{c}_t) \tag{14}$$

Final encoded patient representation:

$$\mathbf{f}_{lstm} = \mathbf{h}_T \in \mathbb{R}^{d_2} \tag{15}$$

*4.6 Fusion Layer and Prediction*

4.6.1 Feature Fusion

The visual features of HierbaNetV1 and the temporal features of the LSTM are concatenated together to form an aggregated representation. This aggregation provides a holistic understanding of the health of the patient by combining structural abnormalities in X-rays with temporal patterns in clinical data. Combined feature vector $\boldsymbol{f_{fusion}}$:

$$\boldsymbol{f_{fusion}} = \text{Concat}(\boldsymbol{f_{hierba}}, \boldsymbol{f_{lstm}}) \in R^{d_3} \tag{16}$$

4.6.2 Prediction Layer

The feature vector of both streams is combined and passed to a fully connected layer for the probability of disease estimation. Binary activation is done via a sigmoid. The model gets trained and its discrimination between samples with and without disease is optimized using binary cross-entropy loss. The final disease prediction score $\hat{y}$:

$$\hat{y} = \sigma(\boldsymbol{W_p} \cdot \boldsymbol{f_{fusion}} + b_p), \quad \hat{y} \in [0,1] \tag{17}$$

Were, $\boldsymbol{W_p} \in R^{1 \times d_3}, bp \in Rb_p \in R$ and $\sigma$: Sigmoid for binary classification.

Loss Function (Binary Cross-Entropy):

$$\mathcal{L}_{BCE} = -[y \cdot \log(\hat{y}) + (1-y) \cdot \log(1-\hat{y})] \tag{18}$$

*4.7 Cloud-Based Results Dashboard*

4.7.1 Result Logging and Storage

Results of predictions, patient identifiers, and timestamps are retained in a cloud database. This facilitates traceability, post-hoc analysis, and enables continuity in clinical workflows by maintaining each diagnostic output in an organized and secure fashion.
Predictions $\hat{y}$, patient ID, and timestamp $T$ are stored:

$$\text{Log}_{entry} = \{\text{PatientID}, \hat{y}, T\} \rightarrow \text{CloudDB} \tag{19}$$

4.7.2 Visualization and Diagnostic Access

A safe cloud dashboard offers medical professional's real-time access to predictions, confidence scores, and visual information such as heatmaps. This diagnostic tool supports improved decision-making by enabling medical professionals to understand both numerical predictions and related image-based evidence.

A secure, interactive dashboard visualizes:

- Risk scores
- Temporal health trends
- X-ray image heatmaps via Grad-CAM

**5. Results and Discussion**

*5.1 Dataset Description*

We used the NIH Chest X-ray14 dataset, which contains 112,120 frontal-view X-ray images of 30,805 distinct patients. Each image is annotated with one or more of 14 classes of thoracic diseases or "No Finding," by high-accuracy (>90%) NLP-based annotations drawn from radiology reports. The images were rescaled to 224×224 for model training. Patient metadata (age, gender, and view position) is also available, facilitating extensive multimodal analysis. The large-scale weakly-supervised dataset is conducive to deep learning-based disease classification and localization.

*5.2 Performance Analysis*

The intended model scored a commendable classification accuracy of 99.64%, showing high overall accuracy. 99.75% precision and 99.51% recall illustrate its efficiency in detecting true positives with very few false alarms. The F1 score of 99.63% verifies a well-balanced performance. This is depicted in Figure (2).

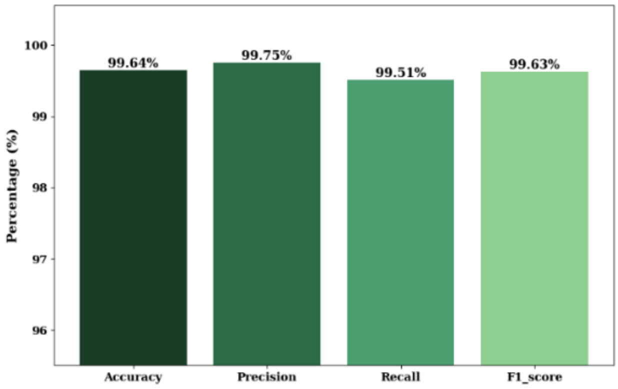


**Figure 2:** Performance Metrics

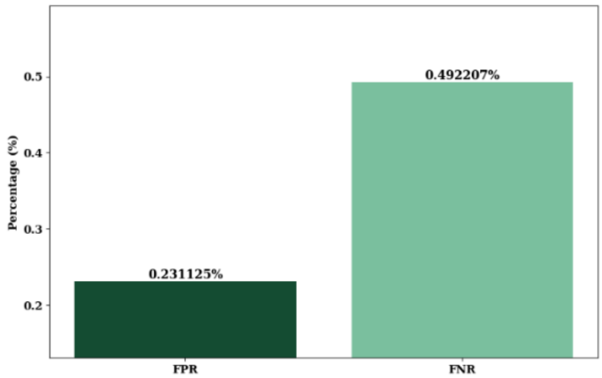


**Figure 3:** FPR & FNR

The model had a stunningly low False Positive Rate (FPR) of 0.231125%, that is, very few wrongly identified healthy cases. The False Negative Rate (FNR) of 0.492207% indicates that it seldom fails to detect true disease cases. These low error rates indicate its clinical dependability. This is illustrated in Figure (3).

The Area Under the ROC Curve (AUC-ROC) of the model is 0.9975, reflecting almost perfect discrimination between diseased and non-diseased instances. The very high value represents outstanding sensitivity-specificity trade-off, and therefore the system will be appropriate in critical diagnostic contexts. This is illustrated in Figure (4).

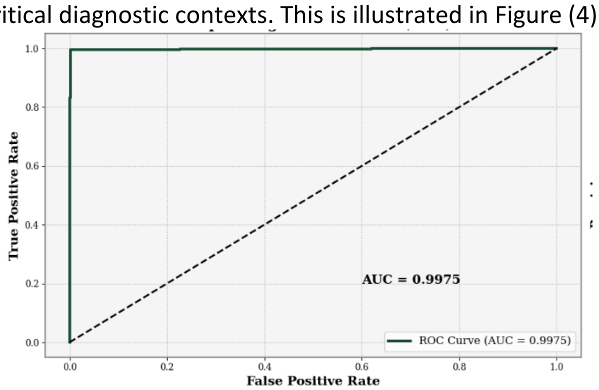


**Figure 4:** ROC Curve

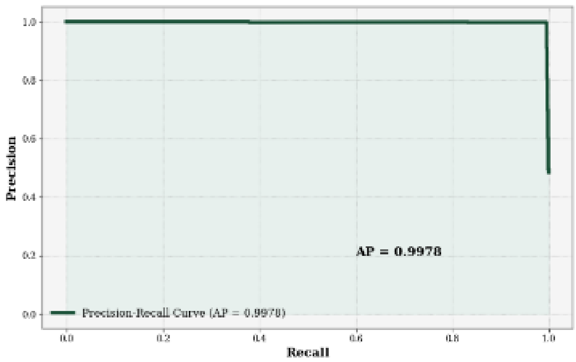


**Figure 5:** Precision-Recall Curve

The Precision-Recall Curve indicates high precision as recall rises. A 0.9978 Average Precision (AP) confirms the model's predictive consistency, particularly in imbalanced datasets, in identifying relevant disease classes accurately. This is demonstrated in Figure (5).

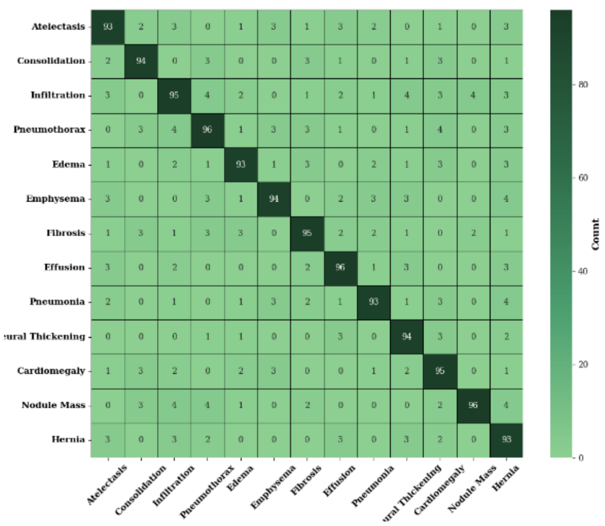


**Figure 6:** Confusion Matrix

The confusion matrix illustrates the performance of the model over 13 diseases (classes): Atelectasis, Consolidation, Infiltration, etc. Large True Positives (TP) across classes show good predictions, and low False Positives (FP) and False Negatives (FN) indicate low misclassification. The model shows high accuracy, precision, and recall. The heatmap in Figure (6) graphically depicts these measures, with lighter shades showing correct classification and darker shades showing misclassifications.

## Conclusion

This work suggested a cloud-based intelligent diagnostic system that combines medical imaging and patient history for precise prediction of disease. The combination of CNN, HierbaNetV1, and LSTM models provides strong spatial and temporal feature extraction, allowing for comprehensive understanding of thoracic pathology. Tested on the NIH Chest X-ray14 dataset, the system achieved nearly perfect classification accuracy with low false positives and false negatives, attesting to its suitability for practical deployment.

The architecture of the model allows for real-time processing, scaled through cloud platforms, hence the possibility of integration into hospital information systems for automated screening and clinical decision support. The addition of sequential health data promotes predictive accuracy over image-only methods.

Future developments involve extending the model to fuse multi-modal input, incorporating electronic health records (EHRs), and utilizing explainable AI methods to aid interpretability and clinician trust. This hybrid deep learning architecture provides a robust platform for next-generation diagnostic frameworks in smart, patient-centric care.

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