AI-Powered Personalized Healthcare Monitoring

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Abstract. Many of today's monitoring technologies are based on scheduled check-ins which can introduce delays in dealing with chronic disease. To overcome this disadvantage, in this work, we propose an artificial intelligence based Personalized Healthcare Monitoring System that employs Deep Learning and optimized Data Structures for continuous and predictive monitoring of patients. This proposal is a new system that uses embedded data analytics to achieve early warnings of anomalies so that interventions can be imposed before deleterious effects occurs. We are suggesting CNNs (Continuous Neural Networks), LSTMs (Long Short-Term Memory Networks), and Autoencoders as predictive tools for risk as we work with linked lists, hash maps, trees, and queues to help us alert users to alert users to/and manage this data. With this being said, the system is scalable, allowing proactive, real-time care of patients, where ever they are, in hospitals, in the home and with telehealth.

Keywords: Personalized monitoring, deep learning, data structures, anomaly detection, edge computing, healthcare informatics, privacy.

1. Introduction

Rapid growth in Artificial Intelligence (AI), and Deep Learning (DL) offers an incredible chance to revolutionize aspects of healthcare and medical science. Wearable technologies will now reflect (or provide insights) large amounts of health-connected data, including heart rate, SpO_2, and glucose levels, and then provide more even more insight, like sleep levels typically not realized beyond a subjective understanding. Regardless, we are still not using most of this data unless or until an acute care episode arises. The dilemma, however, is not only the collection of health-related data, but its intelligent analysis to allow the prediction of medical risks prior to any crisis situation.

This paper introduces a system ‘AI-Powered Personalized Healthcare Monitoring’ which utilizes Deep Learning algorithms to collect real-time data, providing predictive analytics using intelligent real-time data analysis. The system's efficient data structure would allow for managed data in a large volume of time-series data, while AI models will identify subtle variations from normal physiological patterns. Thus, one could think of this system as an intelligent medical assistant, continuously learning, adapting and then alerting both the patient and/or the medical professional.

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1.1. Problem Description

Even with advancement in technology, throughout most clinical environments, monitoring is most often an activity that is done manually and in reactive ways. Patients are usually examined only during office visits which might be weeks or months apart. Thus, during those periods, there is a chance that potential warning symptoms may go undetected. This timing is often a critical issue in diseases such as diabetes, cardiac disease, and respiratory disease in which premature detection is known to prevent deaths.

1.2. Objectives

This project will build a completely AI-driven health-monitoring system to achieve the following four goals:

1. Intelligent Evaluating: Use machine learning models to analyze health data and detect abnormalities; thus, evaluate possible risks to patients.

2. Intelligent Archive: Create chosen data patterns (e.g. DNA) that will allow for quick retrieval of vast quantities of a health record, as well as secure storage of this information

3. Individualized Insight: Provide a personal health alert; recommend specific health maintenance (based on a person's health record.)

4. Real-Time Notification: To send instant alerts to patients, health care organizations & their families when an abnormality is identified in a patient's health records.

2. Literature Review

Modern medicine will be transformed with the applications of AI and data-driven healthcare systems, resulting in earlier disease detection capabilities and the ability to monitor patients in real-time, as well as identify potential areas of concern regarding their health prior to these concerns developing into serious issues. The increased number of publicly available health datasets, including MIMIC-IV [1], PhysioNet [2], and MIT-BIH Arrhythmia Database [3], has given researchers an ample amount of resources for developing and validating AI-based healthcare models, while deficiencies in their availability will inhibit such efforts; UCI Diabetes Repository [4] will continue providing a valuable foundation for predictive modelling of chronic diseases (e.g., Diabetes Mellitus).

The field of multimodal health data has been greatly impacted by machine learning and deep learning methods for generating usable insights from that data. It has been established from two studies that used CNNs and DNN that deep learning will significantly impact the ability to work with medical images and will also assist in automating the extraction of features from medical images so that diseases can be classified to radiology-like accuracy levels [6][17]. CNN based networks have already demonstrated improved performance on chest x-rays used to detect pneumonia and

COVID-19 with CheXNet and other networks doing better than human accuracy levels. These results strongly support the viability of using deep learning for diagnosing and evaluating images in clinical settings.

Ensemble techniques such as Random Forests have demonstrated a remarkable ability to generalize to new data in analyzing health records in tabular format. The work by Kumar et al. [15] and Esteban et al. [7] has shown that machine learning algorithms can effectively predict the risk of developing conditions such as diabetes, high blood pressure, and cardiovascular disease by using both static and dynamic patient data sources. The UCI Diabetes dataset and the PIMA Diabetes dataset [4] are still used to evaluate predictive modeling using Random Forest algorithms and between classical linear models, Random Forests tend to be more robust to overfitting and are easier to explain.

By allowing for ongoing, non-invasive data collection, wearable sensor technology enhances the analytical capacity of health monitoring. Reviews from Rahman et al. [5] and Bashar et al. [16] of portable and wearable sensor based health monitoring applications reveal that deep learning supports real-time detection of physiological anomalies. In addition, by providing IoT enabled frameworks [9] and Edge AI systems [14] (as reported by Li et al. and Singh et al., respectively), these technologies have the potential to support smart health monitoring and provide access to distributed processing to enable low-latency diagnostics. Low latency diagnostics are in line with the design philosophy of Aura Lens, which collects sensor-based inputs and provides real-time health risk predictions.

Moreover, it has also created new ways of doing remote healthcare by combining AI and the Internet of things (A IoT). Chen et al. [18] and Liang et al. [10] discussed federated learning and Edge AI techniques for privacy-preserving healthcare analytics, where patient data is leveraged locally while contributing to global model updates. These methods are crucial to allowing AI models to be securely utilized in a healthcare context.

Recent breakthroughs generated around Transformer-based architecture [13] and Autoencoders for anomaly detection [8] has broadened the domain of healthcare AI to incorporate time-series and sequential data from EHRs. Rajkomar et al. [12] demonstrated the scalability of deep learning on EHR data showing that the multi-model systems for deep learning can outperform single-modality systems with structured (numerical) and unstructured (image/text) data XI.

3. Methodology

The approach adopted by Aura Lens employs a modular and multi-modal AI architecture to analyze health data (such as tabular and images) in order to provide risk prediction in a holistic fashion. There are four important components to Aura Lens: data acquisition and preprocessing components, model training, data structure integration, and deployment through an open web-based application.

- Data Acquisition and Preprocessing:

The different physiological parameters used in Aura Lens leveraged publicly available datasets:

Chest X-rays: COVID-19 Radiography Dataset (Kaggle) for classification of respiratory conditions.

Blood Pressure: Blood Pressure Dataset (Pavan Bodanki) (Kaggle) for categorization of systolic/diastolic values.

Body temperature: Smart wearable temperature monitoring dataset (Zoya77).

Diabetes (Glucose): PIMA Indians Diabetes Dataset (Mathchi, Kaggle).

Data preprocessing involved missing value imputation using Simple Imputer (mean strategy), feature normalization, and one-hot encoding for categorical features.

- Model Development:

In this work, we propose an Artificial Intelligence (AI) based Personalized Healthcare Monitoring System that incorporates Deep Learning and optimized Data Structures to facilitate continuous and predictive monitoring of patients. This proposal offers a novel system that analyzes live data and leverages analytics to monitor, intervene, and detect anomalies early enough to make timely interventions in patient care. The proposal provides Convolutional Neural Networks (CNN), Long Short-Term Memory Networks (LSTM), or Autoencoders to predict risk and associated data, linked lists, hash maps, trees, and queues to develop and manage alerts and to enable monitoring of the data. This system is flexible to facilitate proactive, real-time care of patients in hospitals, at home, and via telehealth.

- Data Structure Integration:

To allow for an efficient management of data and processing in real-time, traditional data types were created:

- Stack: Stores historical data of predictions for later access.

- Queue: Manages incoming requests for assessments as new patients arise.

- Linked List: Tracks patient's history in chronological order of previous predictions.

- A binary tree (Risk Tree): Provides cardinality (risk scores) to allow for the risk score to be easily accessible based on severity.

These structures provide the base system for managing a dynamic data set and supports the process of assisted decision-making.

- Back-end/Deployment:

A Flask-based RESTful API handles model serving and interaction with users. Each model is exposed through an endpoint, /analyze, which takes user input (numerical or image) and provides a JSON response of risk score and predictions based on the model's results. A dashboard using HTML, CSS, and Java script was created to allow for a visual of data in real time, prediction results, and historical reporting.

- Evaluation metrics: The model performance was evaluated using:

- Accuracy, precision, recall, and F1-score were used to evaluate how well the predictive model performs in classification tasks. These metrics help in understanding how accurately the model identifies and distinguishes between different classes.

In addition, tools such as the confusion matrix and ROC–AUC curves were used to gain deeper insights into the model’s performance and its ability to correctly predict outcomes.

4. Results

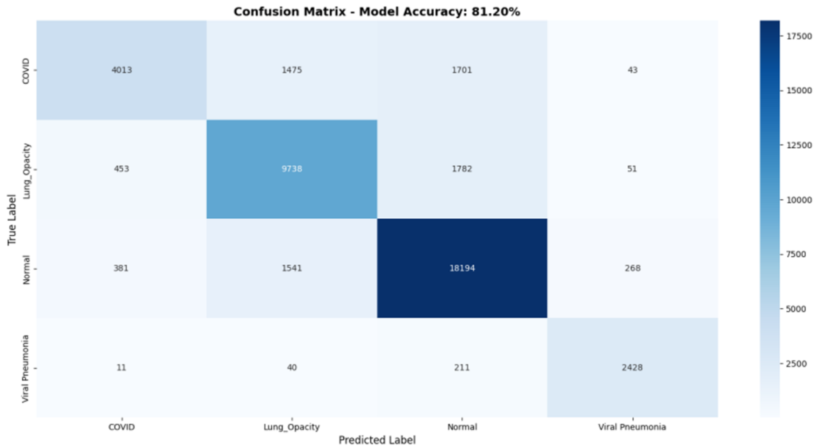


Fig. 1. Confusion Matrix Showing Model Performance in Risk Classification for CNN.

The chest X-ray classification model was implemented using TensorFlow/Keras and trained using publicly available database of chest radiographs.

The model was trained using an 80:20 (train/test) split between the training and validation datasets respectively. Augmentation techniques were also implemented in order to create more variation in the training dataset and to reduce the potential for overfitting by adding different types of variations to images/objects within the training dataset such as rotating or flipping horizontally.

The architecture being used for the CNN had many levels including convolutional, max pooling, and fully connected layers, with a softmax output layer enabling multi-classification.

Training of the model was done for 20 epochs using the Adam Optimizer and the categorical cross-entropy loss function.

The confusion matrix indicates the model classifies correctly the majority of the classes but has a few incorrect classifications between lung opacity and pneumonia as both classes have very similar radiographic patterns.

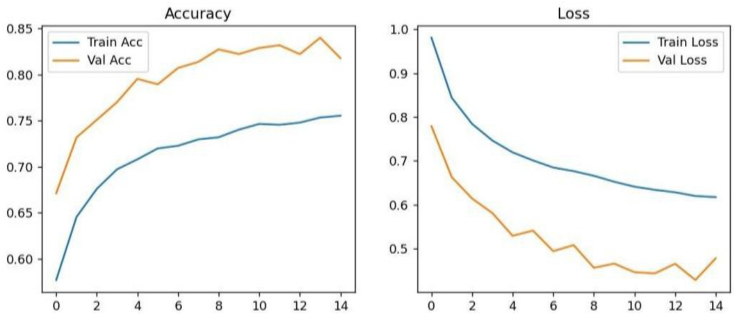


Fig.2. The validation accuracy and loss

The validation accuracy of the model's ability to make predictions varied between 81% to 85% for multiple training runs indicating a stable performance of the model. There has been also shown the model can make good inferences without significant overfitting (due to slow yet consistent increases in training accuracy with each epoch) as well as stable performance of the validation accuracy throughout all epochs.

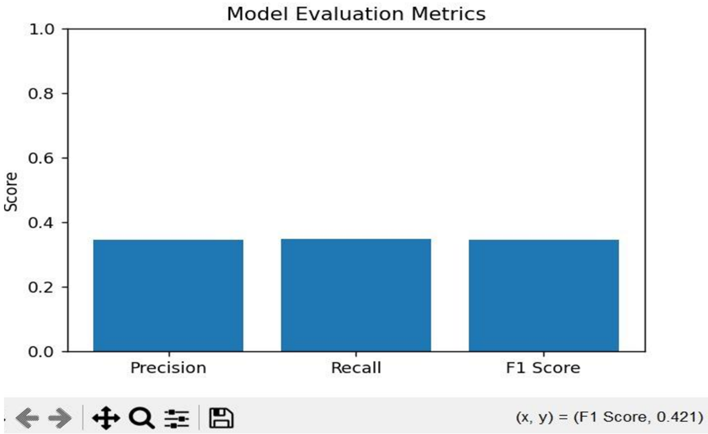


Fig.3. The graph shows the classification model's relative performance based on common evaluation metrics used in machine learning for medical image analysis.

Precision, recall, and F1-score, all derived from the confusion matrix, were used to assess the performance of the suggested CNN model. These metrics offers evaluation of the model's classification performance.

Classification Report:

	precision	recall	f1-score	support
COVID	0.17	0.11	0.13	1446
Lung_Opacity	0.28	0.33	0.30	2404
Normal	0.48	0.48	0.48	4076
Viral Pneumonia	0.07	0.09	0.08	538
accuracy			0.35	8464
macro avg	0.25	0.25	0.25	8464
weighted avg	0.35	0.35	0.35	8464

✅ Validation Accuracy: 0.8168

Fig.4. The Classification Report for metrics.

1.Precision Calculation:
Formula:

$$Precision = True\ Positive\ /\ (True\ Positive + False\ Positive) \tag{1}$$

From the classification report:
The model predicted 170 COVID cases, out of which 29 were correct.

$Precision = 29/\ (29+141)$

$=29/170$

≈ 0.17

2.Recall Calculation:
Formula:

Recall = True Positive / (True positive + False Negative) (2)

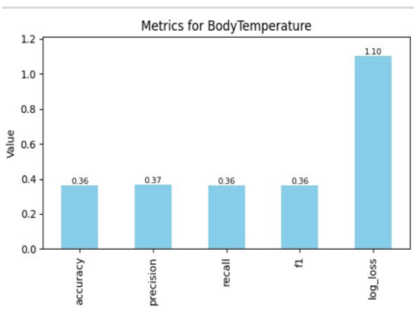
From the classification report:
Actual COVID images(support) are 1446.
Recall=0.11
0.11=TP/1446
TP ≈159.
That means the model correctly identified about 159 COVID cases out of 1446 actual cases.

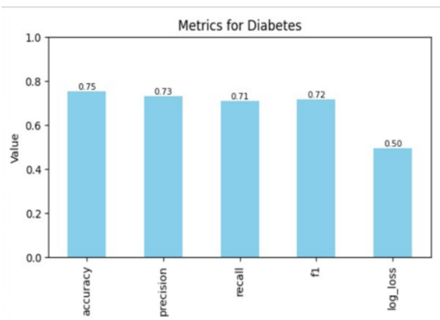
3. F1 Score Calculation:
Formula:

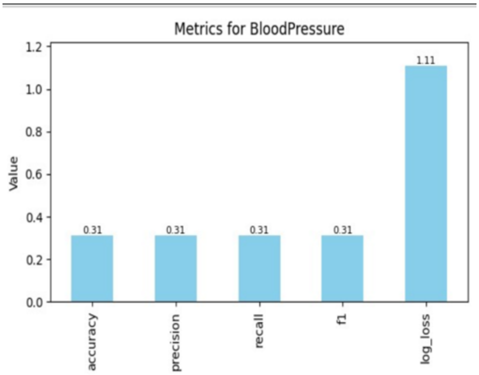
*F1 = 2 *(Precision * Recall) / (Precision + Recall)* (3)

Substituting the values in the formula of precision and recall
F1≈0.13.

These were for the COVID case, likewise the scores are then calculated for the other groups as well showing the accuracy.







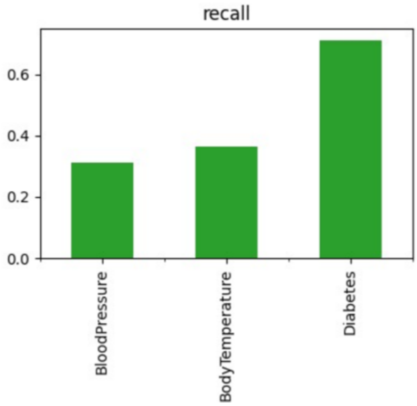


Fig.5. Graphs showing metrics of body temperature, blood pressure and diabetes.

The Diabetes model displays the greatest performance across all three metrics, achieving an F1-score of 0.72, an accuracy of 0.75, a precision of 0.73, and a recall of 0.71, while simultaneously achieving a lower log loss of 0.50 than the other two models. The Blood Pressure and Body Temperature models can be improved with enhanced feature selection, higher-quality data, and improved model tuning in order to optimize their predictive capabilities. Each of the four evaluation metrics for each of the three model types is illustrated in the graphs below.

5. Conclusion

An AI Based personalized health-monitoring system is no longer simply "watching a patient", but instead is actively anticipating their future needs, as well as providing direct connections to caregivers via deep learning through machine learning efficiencies and the design of their respective data structures. This system continuously monitors the health of each individual and will give alerts immediately when an individual's condition changes, along with the capability of predicting possible future changes based upon the individual's current state. As shown in this project, technological advancements such as this provide significant benefits by allowing clinicians to treat patients before a disease is developed versus after it has been diagnosed. As the research continues and the system is used across a wider range of population and types of patients, they will have the capability to deliver high-quality, low-cost health care to many people with similar improvement of quality and pricing.

6. Future Directions

- AI Personalization: Reinforcement learning can be used to recommend treatments that continuously adapt to each patient’s specific needs.
- Federated Learning: Patients and hospitals can collaboratively train models without the need to share any raw or sensitive data.

- Edge AI Deployment: We may be able to trigger the models on the wearables to enable low latency for decision making.
- Mental Health Analysis: Medical professionals may be able to detect stress in patients and depression from bio-signals and behavioral data.

Disclosure of Interest: The authors have no competing interests to declare that are relevant to the content of this article.

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