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Deep Learning Model for Diagnosis of Chronic Diseases

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Abstract: The increasing prevalence of chronic diseases and aging populations has created significant challenges for healthcare systems worldwide. To meet these challenges, there has been a growing interest in leveraging advanced technologies, such as data fusion and cloud storage, to enable more efficient and effective healthcare services. The design methodology employed for this innovative system is object-oriented analysis and design, providing a structured and systematic framework for the development process. Furthermore, the utilization of the Python programming language enhances the system's efficiency, scalability, and maintainability. By integrating a data fusion model, the system combines data from multiple sources to provide a more accurate and holistic view of patient health, thus enhancing the diagnostic process. This fusion of diverse data types, coupled with the robust CNN architecture, ensures a high level of precision and reliability in disease detection. This dissertation highlights an approach to conducting checks on various chronic diseases, including malaria, typhoid, heart disease, diabetic retinopathy, liver disease, and fetal health, utilizing Convolutional Neural Networks (CNN). The developed model exhibits an exceptional accuracy rate of 99.98%, underscoring its effectiveness in disease detection. The findings of this research represent a significant leap forward in leveraging advanced technologies for precise and comprehensive chronic disease diagnostics, with implications for improving healthcare outcomes and patient well-being.

Keywords: Smart Health Care, Data Fusion, Chronic Diseases, Convolutional Neural Network

I. INTRODUCTION

Hierarchical data fusion is a critical component in advancing smart health checks by integrating data from various sources to enhance monitoring and decision-making processes. This approach involves combining information at different levels to provide a comprehensive view of an individual's health status. Research by Xue et al. (2020) emphasizes the significance of multi-level data fusion in intelligent medical monitoring to optimize resource utilization, improve work efficiency, and facilitate the construction of hierarchical data in healthcare settings. Similarly, Dautov et al. (2019) focus on hierarchical data fusion in Smart Healthcare, particularly within IoT networks, encompassing edge devices, network units, and Cloud platforms, highlighting the importance of integrating data across different layers for effective health monitoring.

The foundation of Smart Healthcare is built on intelligent, low-power, wirelessly connected medical devices. Therefore, there is a need for a combination of several various data sources, be it streaming or static data Healthcare data comes from various sources with different formats, structures, and semantics, making data integration challenging. This heterogeneity can lead to difficulties in combining and analyzing data comprehensively, impeding the accurate detection and diagnosis of chronic diseases by CNNs.

To this end, doctors typically base their decisions on several examinations, and by performing manual data fusion over these several sources (typically, the more the better), can minimize the uncertainty and, eventually, come to a precise, valid diagnosis (Song *et al.*, 2019).

The implementation of data fusion in healthcare system is not without its challenges. One of the key issues is the need to manage and process large volumes of data from disparate sources, which can be complex and time-consuming. Managing large datasets can strain computational resources, affecting the efficiency and performance of health check systems. Ensuring that CNNs can scale effectively with the increasing data volume is crucial for maintaining accuracy and reliability.

(Scalability). Additionally, healthcare systems often require bidirectional coordination between different entities, such as healthcare providers, patients, and medical devices (CNN) Perez-Pozuelo *et al.* (2020). Another challenge comes from the data's Privacy and Security. Handling sensitive healthcare data necessitates stringent privacy and security measures to protect patient information.

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Data breaches can have severe consequences, including identity theft and loss of trust in healthcare systems. Implementing robust security protocols while maintaining the efficiency and accessibility of the Smart Healthcare System is vital. This problem underscores the need for a comprehensive solution that integrates diverse data sources, scales with growing data volumes, and ensures the privacy and security of patient information, all while utilizing the advanced capabilities of CNNs for accurate and timely diagnosis of chronic diseases.

In summary, hierarchical data fusion and CNN serves as a cornerstone in enabling smart health checks by amalgamating data from diverse sources to provide comprehensive insights into individuals' health status. These will be achieved by, designing a user-friendly interface for quick and easy access to patient records as well as integrating and analyzing multi-modal data sources in a unified framework finally, developing scalable solutions capable of handling large volumes of hierarchical healthcare data efficiently by leveraging multi-level data fusion techniques, healthcare systems can enhance monitoring, diagnosis, and treatment processes, ultimately improving patient outcomes and healthcare delivery efficiency. The integration of advanced technologies like blockchain, edge computing, and machine learning further enhances the capabilities of data fusion in smart health applications, paving the way for more effective and secure health monitoring systems. The implementation would be carried out using python programming.

II. LITERATURE REVIEW

Ihnaini et al. (2021) proposed a smart healthcare recommendation system for multidisciplinary diabetes patients. The system utilizes deep ensemble learning with data fusion techniques to predict and recommend accurate diagnoses for diabetic diseases. Although the paper does not provide specific accuracy values, it emphasizes the use of optimal machine learning models to improve the accuracy of disease prediction.

Abbas et al. (2023) proposes a novel methodology called fused weighted federated deep extreme machine learning (FW-FDEML) to enhance the prediction of lung disease, particularly cancer, inside the smart healthcare sector 5.0 framework. The study showcases the superiority of the FW-FDEML model over current cutting-edge techniques, achieving an astounding accuracy of 97.2% using MATLAB 2020a for simulation and data analysis. This notable progress underscores the potential of the model to improve prediction abilities in smart healthcare, therefore aiding in more efficient and timely therapies for lungs illness.

Muhammad & Alhussein (2021) suggests a vocal pathology detection system that is part of a smart healthcare framework. This system uses Internet of Things (IoT) devices such as microphones and electroglottography (EGG) devices to record voice and EGG data. The data undergo conversion into spectrograms and are subsequently analyzed by a pre-trained convolutional neural network (CNN) to extract distinctive characteristics. Subsequently, these characteristics are combined and examined via a bi-directional long short-term memory (LSTM) network. The system's performance was evaluated using the publicly accessible Saarbruecken voice database. It achieved a commendable accuracy of 95.65%. The results suggest that the bimodal input, which combines both voice and EGG signals, beats systems that use only a single input.

Farooq et al. (2022) present a blockchain-based smart home network security system empowered with fused machine learning, demonstrating the application of data fusion at the decision level to enhance security and accuracy in healthcare data management. Gumaei *et al*. (2019) developed a hybrid deep learning model for human activity recognition using multimodal body sensing data. The model combines different machine learning techniques to accurately recognize and classify various human activities based on data collected from multiple sensors. This multimodal approach involves integrating data from sources such as accelerometers, gyroscopes, and physiological sensors to provide a holistic view of the user's physical activities. By leveraging the strengths of multiple machine learning algorithms, the hybrid model can achieve higher accuracy and robustness in activity recognition compared to single-method approaches. The importance of this research lies in its application to smart healthcare systems, where accurate human activity recognition is crucial for monitoring and assessing patient health. Ihnaini *et al*. (2021) proposed a smart healthcare recommendation system specifically designed for multidisciplinary diabetes patients. This innovative system utilizes deep ensemble learning combined with data fusion techniques to provide accurate predictions and recommendations for managing diabetic diseases. The approach involves integrating data from various sources, such as electronic health records, wearable devices, and patient-reported outcomes, to create a comprehensive dataset. This enriched dataset is then used to train the ensemble learning models, which combine the strengths of multiple machine learning algorithms to enhance predictive accuracy and reliability. By leveraging deep learning and data fusion, the system can identify subtle patterns and correlations in the data that may not be apparent through traditional analysis methods. Although the paper does not provide specific accuracy values, the emphasis is on the system's capability to improve the accuracy of disease prediction and management, ultimately enhancing patient outcomes. Furthermore, the integration of data fusion techniques with emerging technologies like blockchain and edge computing is gaining traction in the smart health domain.

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Mortazavi et al. (2016) conducted a comparison of machine learning models (random forests, boosting, and hierarchical combinations) and standard logistic regression (LR) in order to predict readmissions for all-cause and heart failure within 30 and 180 days. By employing a derivation and validation set that underwent 100 bootstrapped iterations, it was determined that random forests outperformed LR by 17.8% in predicting 30-day all-cause readmissions (with a mean C statistic of 0.628 compared to 0.533). Boosting increased the average C statistic by 24.9% for heart failure readmissions, with values of 0.678 and 0.543. Random forests demonstrated a broader range of predictive capabilities, with readmission rates ranging from 7.8% to 26.2% in the lowest and highest deciles, respectively. In comparison, LR had readmission rates ranging from 14.2% to 16.4%. Abbas et al. (2023) presents a novel approach called fused weighted federated deep extreme machine learning model for predicting lung cancer disease in smart healthcare systems. The objective of the model is to deliver precise forecasts and enhance healthcare results. Lavanya *et al*. (2023) presents a comprehensive review of recent advances in detecting elderly behaviours using deep learning techniques within the context of healthcare. The paper outlines various methods and approaches that have been developed to monitor and analyze the activities and behaviors of elderly individuals. These techniques leverage deep learning algorithms to process data from various sources, such as wearable devices, smart home sensors, and video surveillance systems. The primary objective is to identify patterns and anomalies in behavior that could indicate health issues, such as falls, cognitive decline, or changes in daily routines, enabling timely interventions and support.

The work by Almutairi et al. (2022) examines the latest developments, techniques, practical implementations, and obstacles in using deep learning to identify elderly habits in healthcare. The text focuses on the application of deep learning techniques to enhance the quality of life for elderly folks in society.

Nweke *et al*. (2019) investigate the use of multiple classifier system techniques and data fusion methods for human activity recognition (HAR) in mobile and wearable devices. The study emphasizes the application of deep learning fusion techniques, highlighting their strengths and identifying their limitations. By combining data from various sensors embedded in mobile and wearable devices, the authors aim to create a more accurate and reliable HAR system. The use of deep learning models allows the system to learn complex patterns and interactions between different types of sensor data, leading to improved activity recognition.

III. METHODOLOGY

The architecture of the proposed system can be seen in Figure 1. It comprised of various components and how the connected to each other in forming hierarchical smart health care system for chronic disease checks.

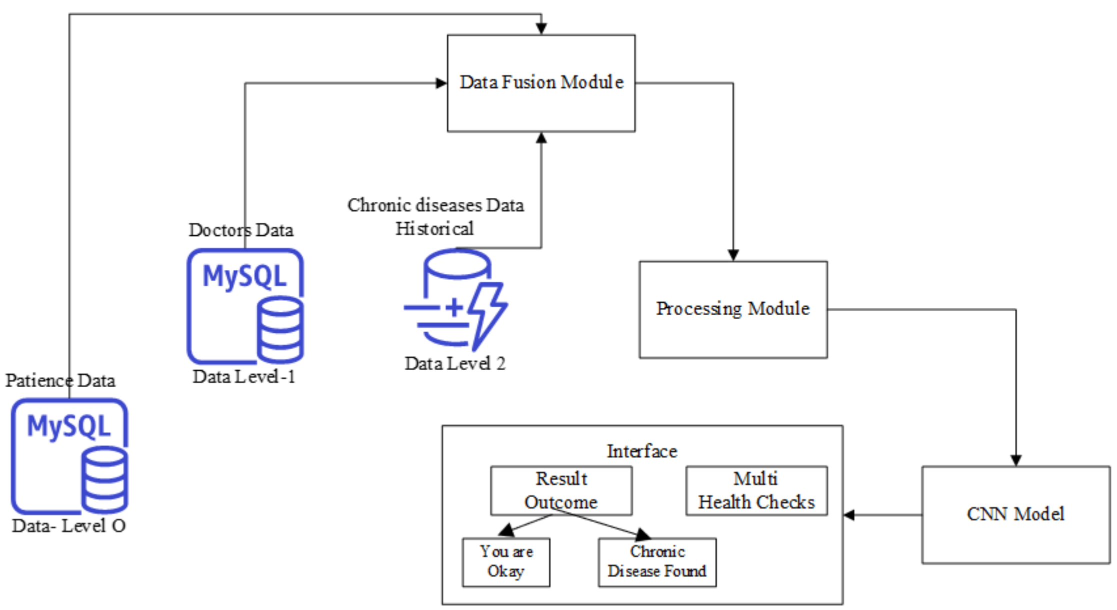

Figure 1: Architecture of the Proposed System

Data Fusion Module: The data fusion module integrates and synthesizes data from multiple sources to provide a comprehensive and coherent understanding. The following are the various data used:

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i. **Data Level 0 (Patient Information):** This component involves the collection, storage, and management of individual patient data. It includes personal details, medical history, allergies, medications, and other relevant information. This data is crucial for creating personalized healthcare plans.

ii. **Data Level 1 (Doctors Information):** At this level, information about healthcare professionals is stored. This includes details like their qualifications, specializations, availability, and experience. It helps in assigning the right doctor for a particular patient based on their needs.

iii. **Data Level 2 (External Data):** This component involves the integration of external datasets related to specific health conditions like malaria, cancer, kidney diseases, fetal health, and heart diseases. These datasets provide a broader understanding of various health conditions and assist in making more accurate diagnoses and treatment plans.

iv. **Processing Module:** The processing module helps in filtering and converting the data to suitable readable format for building a model.

Machine Learning (Convolutional Neural Network Model): A Convolutional Neural Network (CNN) is a highly effective deep learning technique that can be utilized in the healthcare field for predictive forecasting. Within this particular framework, it can be employed for purposes like as forecasting illnesses, evaluating potential hazards, and providing suggestions for medical interventions.

In the case of diabetes prediction, the model can use information from Data Level 0 and external diabetes datasets (Data Level 3) to forecast the probability of a patient developing diabetes. The CNN model is trained using past data, enabling it to identify and utilize patterns for making predictions regarding new patients.

Health Checks: Health checks involve the process of assessing a patient's health condition using various tests and examinations. This can include heart checks (e.g., ECG, blood pressure monitoring), kidney checks (e.g., blood tests, ultrasound), cancer checks (e.g., mammograms, biopsies), malarial checks (e.g., blood smears, rapid diagnostic tests), and fetial checks (e.g., ultrasound scans, fetal monitoring).

The results from these health checks, along with the patient's historical data (from Data Level 0) and external datasets (from Data Level 3), can be used as inputs for the CNN model to provide more accurate and personalized healthcare recommendations.

3.1 Component Design

This demonstrates the detailed analysis of the deep learning model in doing evaluations of chronic illnesses. Figure 2 illustrates the sub-components of the CNN model. It illustrates the progression from one layer to the next, culminating in the ultimate layer known as the output layer.

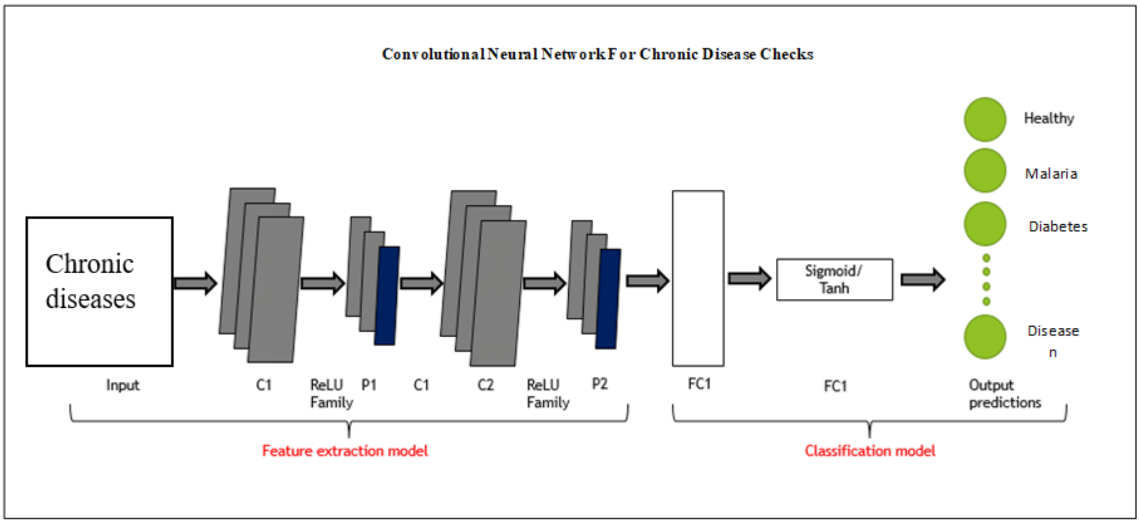

Figure 2: Component design of the Deep learning model (CNN).

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IV. RESULTS AND DISCUSSION

4.1 Data Analysis for Diabetes, Malarial and Typhoid Dataset

This session discusses how the medical images were read into the working directory (Jupiter Notebook) and also how it was processed specifically out-listing typhoid as the data focus however there were several data of different diseases incorporated into the model. The directory path was created using the python function os.path and os.list_dir(). This was used in reading the medical images from the path where they were saved and visualizing the images.

The images were also pre-processed by bringing the data into a balanced form. Figure 3 shows a bar plot for imbalanced data and Figure 4 shows a bar plot of the balanced data. Figure 5 shows a pair plot of the typhoid dataset. Figure 6 shows a plot of the total number of women and male in the in the typhoid dataset. Figure 7 shows the age differences that is most affected by the disease.

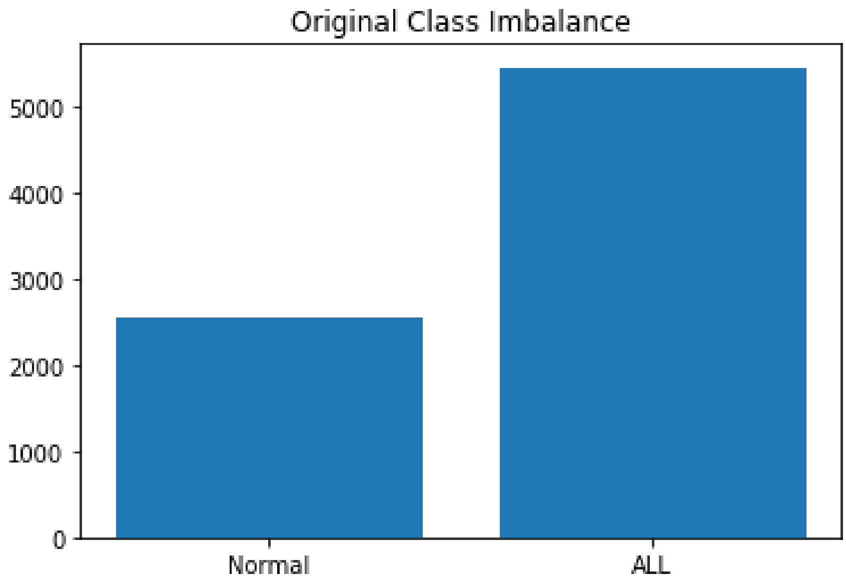

Figure 3: Count plot of Imbalanced data.

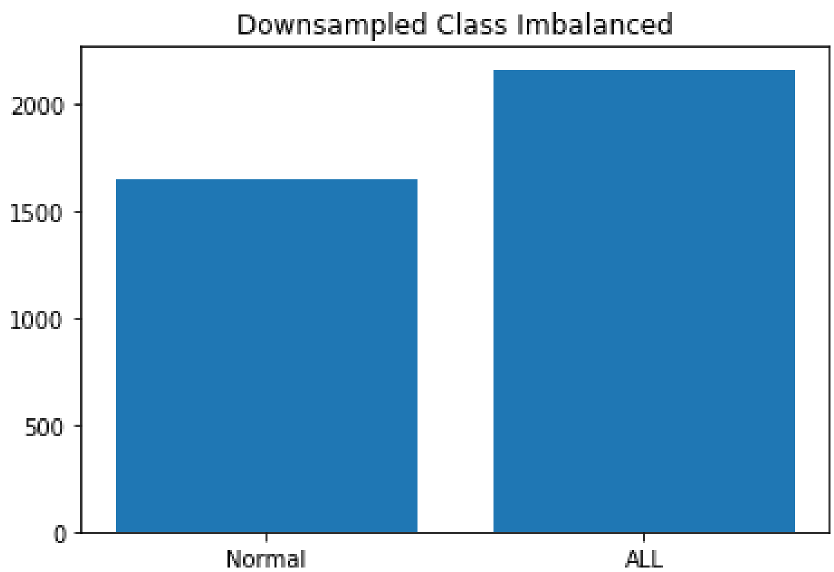

Figure 4: Count plot of Down sampled Data

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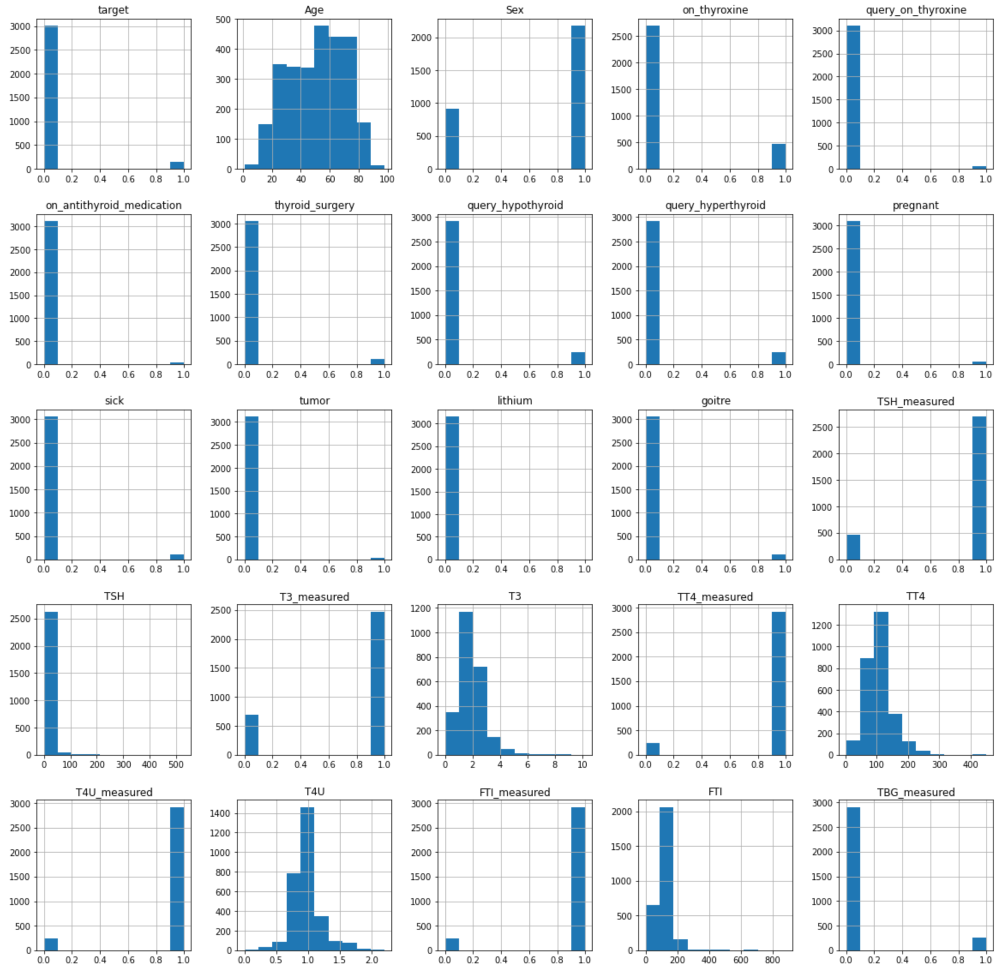

Figure 5: Pair plot of the Typhoid Dataset (https://www.kaggle.com/datasets/stmarcus528/typhoid-fever-dataset)

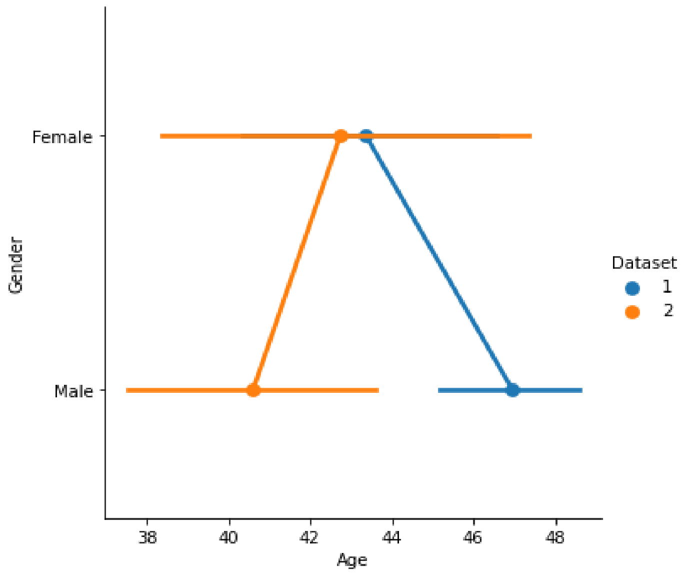

Figure 6: Genger Occurrences in the Typhoid Dataset.

This is a visualization of gender and Age from the typhoid dataset. This was achieved using matplotlib library in python

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4.2 Model Training with a Convolutional Neural Network

This sub-section discusses how the convolutional neural network model was trained using the pre-processed data as input. The convolutional network model was created using three layers (one input layer, one hidden layer, and an output layer). The CNN model architecture used the following parameters:

ZeroPadding2d: This was used to process symmetrically adding zeroes to the input matrix.

Maxpolling2d: This was used to help reduce overfitting, and activation functions Relu for the second layer and SoftMax for the third layer.
The model summary can be seen in Figure 8. The CNN model was trained on a training step of 50, batch size of 198. A sample of the training process can be seen in Figure 9. The training accuracy, loss, precision, and recall of the 2d CNN model can be seen in Figures 10, 11, 12, and 13. Figure 14 shows the confusion matrix.

Model: "CNN"

```
Layer (type) Output Shape            Param #
===========================================================
Zero_padding3d (ZeroPadding3 (None, 104, 104, 3)      0
Conv3d (Conv2D) (None, 100, 100, 30)      2280
Zero_padding3d_1 (ZeroPaddin (None, 104, 104, 30)      0
Conv3d_1 (Conv2D) (None, 100, 100, 30)      22530
Max_pooling3d (MaxPooling2D) (None, 50, 50, 30)      0
Flatten (Flatten) (None, 75000)            0
Dense (Dense) (None, 2)            150002
Activation (Activation) (None, 2)            0
===========================================================
Total params: 174,812
Trainable params: 174,812
Non-trainable params: 0
```

Figure 7: Model Summary

```
Epoch 1/150
37/37 [==============================] - 1s 35ms/step - loss: 0.6996 - acc: 0.5398 - precision: 0.5398 - recall: 0.5398 - auc: 0.5543 - val_loss: 0.
6633 - val_acc: 0.5569 - val_precision: 0.5569 - val_recall: 0.5569 - val_auc: 0.6968
Epoch 2/150
37/37 [==============================] - 1s 19ms/step - loss: 0.6186 - acc: 0.6907 - precision: 0.6907 - recall: 0.6907 - auc: 0.7611 - val_loss: 0.
6354 - val_acc: 0.6436 - val_precision: 0.6436 - val_recall: 0.6436 - val_auc: 0.6786
Epoch 3/150
37/37 [==============================] - 1s 18ms/step - loss: 0.5545 - acc: 0.7356 - precision: 0.7356 - recall: 0.7356 - auc: 0.8073 - val_loss: 0.
5499 - val_acc: 0.7153 - val_precision: 0.7153 - val_recall: 0.7153 - val_auc: 0.8060
Epoch 4/150
37/37 [==============================] - 1s 18ms/step - loss: 0.4793 - acc: 0.7856 - precision: 0.7856 - recall: 0.7856 - auc: 0.8633 - val_loss: 0.
4714 - val_acc: 0.7772 - val_precision: 0.7772 - val_recall: 0.7772 - val_auc: 0.8894
Epoch 5/150
37/37 [==============================] - 1s 18ms/step - loss: 0.4113 - acc: 0.8195 - precision: 0.8195 - recall: 0.8195 - auc: 0.9132 - val_loss: 0.
4420 - val_acc: 0.7772 - val_precision: 0.7772 - val_recall: 0.7772 - val_auc: 0.8835
Epoch 6/150
37/37 [==============================] - 1s 18ms/step - loss: 0.3724 - acc: 0.8441 - precision: 0.8441 - recall: 0.8441 - auc: 0.9253 - val_loss: 0.
4290 - val_acc: 0.7921 - val_precision: 0.7921 - val_recall: 0.7921 - val_auc: 0.8892
Epoch 7/150
37/37 [==============================] - 1s 18ms/step - loss: 0.3333 - acc: 0.8593 - precision: 0.8593 - recall: 0.8593 - auc: 0.9433 - val_loss: 0.
3449 - val_acc: 0.8713 - val_precision: 0.8713 - val_recall: 0.8713 - val_auc: 0.9409
Epoch 8/150
37/37 [==============================] - 1s 18ms/step - loss: 0.2797 - acc: 0.8932 - precision: 0.8932 - recall: 0.8932 - auc: 0.9659 - val_loss: 0.
3177 - val_acc: 0.8663 - val_precision: 0.8663 - val_recall: 0.8663 - val_auc: 0.9484
Epoch 9/150
37/37 [==============================] - 1s 18ms/step - loss: 0.2495 - acc: 0.8975 - precision: 0.8975 - recall: 0.8975 - auc: 0.9738 - val_loss: 0.
2901 - val_acc: 0.8762 - val_precision: 0.8762 - val_recall: 0.8762 - val_auc: 0.9617
Epoch 10/150
37/37 [==============================] - 1s 18ms/step - loss: 0.2188 - acc: 0.9186 - precision: 0.9186 - recall: 0.9186 - auc: 0.9800 - val_loss: 0.
2825 - val_acc: 0.9183 - val_precision: 0.9183 - val_recall: 0.9183 - val_auc: 0.9768
```

Figure 8: Model training of the first 10 steps

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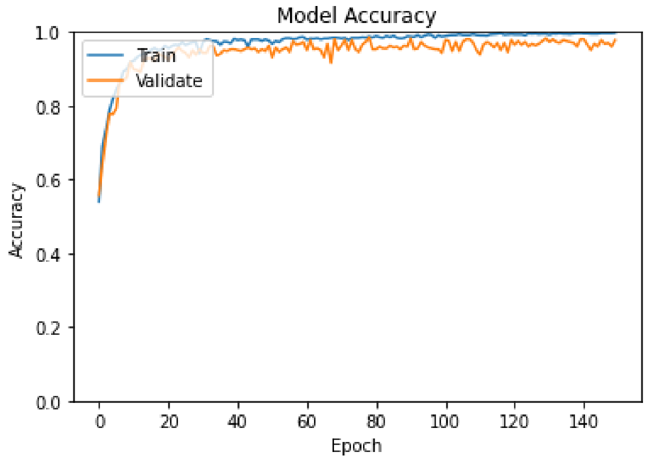

Figure 9: Training accuracy for both training and validation data

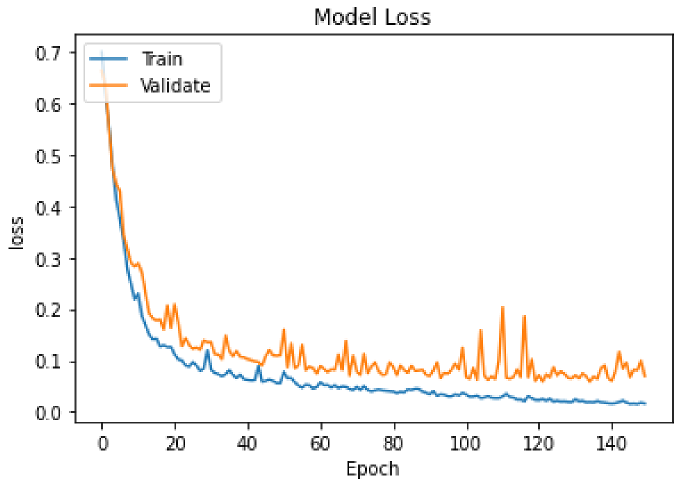

Figure 10: Training loss for both training and validation data.

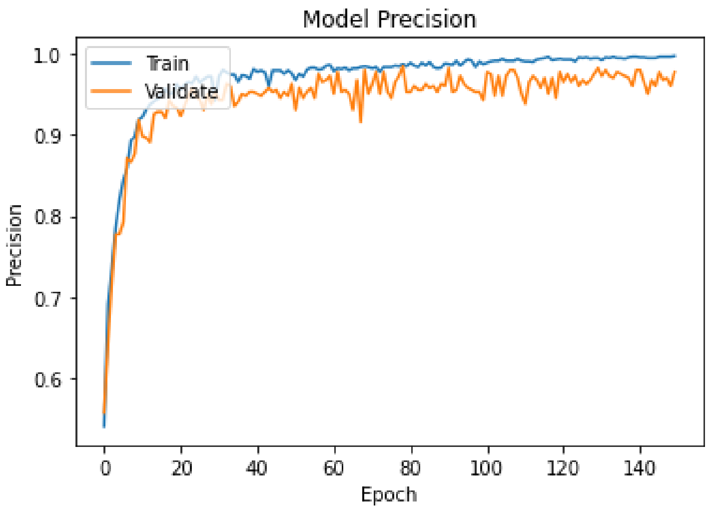

Figure 11: Precision score for both training and validation data.

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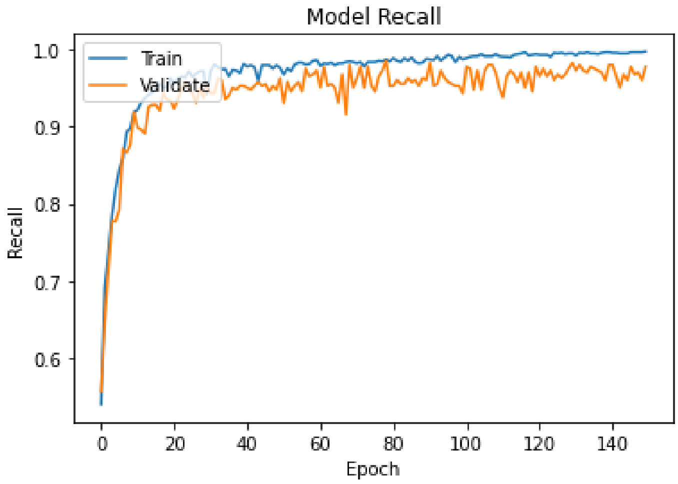
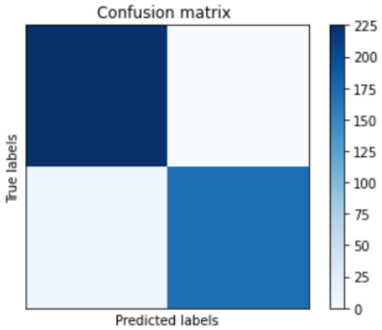


Figure 12: Recall score for both training and validation data.

```
Confusion Matrix: [[225   0]
 [  9 170]]
```




```
True Positives: 170(42.07920792079208%)
False Positives: 0(0.0%)
True Negatives: 225(55.693069306930695%)
False Negatives: 9(2.227722772277228%)
Specificity: 1.0
Misclassification: 9(2.227722772277228%)
```

Figure 13: Confusion matrix of the 3D CNN

	precision	recall	f1-score	support
0	0.90	0.97	0.93	63
1	0.98	0.94	0.96	108
accuracy			0.95	171
macro avg	0.94	0.95	0.94	171
weighted avg	0.95	0.95	0.95	171

Figure 14: Classification report for cancer

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	precision	recall	f1-score	support
No Diabetes	0.74	0.94	0.83	157
Diabetes	0.69	0.30	0.42	74
accuracy			0.73	231
macro avg	0.71	0.62	0.62	231
weighted avg	0.72	0.73	0.69	231

Figure 15: Classification report for Diabetes

	precision	recall	f1-score	support
No Heart Disease	0.88	0.85	0.87	27
Heart Disease	0.89	0.91	0.90	34
accuracy			0.89	61
macro avg	0.89	0.88	0.88	61
weighted avg	0.89	0.89	0.88	61

Figure 16: Classification report for heart disease

	precision	recall	f1-score	support
No-Disease	1.00	1.00	1.00	35
Kidney-Disease	1.00	1.00	1.00	15
accuracy			1.00	50
macro avg	1.00	1.00	1.00	50
weighted avg	1.00	1.00	1.00	50

Figure 17: Classification report for Kidney

Classification Report:

	precision	recall	f1-score	support
Normal	0.56	0.10	0.17	51
Liver Disease	0.72	0.97	0.83	124
accuracy			0.71	175
macro avg	0.64	0.53	0.50	175
weighted avg	0.67	0.71	0.63	175

Figure 18: Classification report for Kidney

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4.3 Integration of the Smart Health Care System

This section shows the smart health system that incorporates the different types of diseases that users can carry out a health check. The homepage of the smart system can be seen in Figure 20

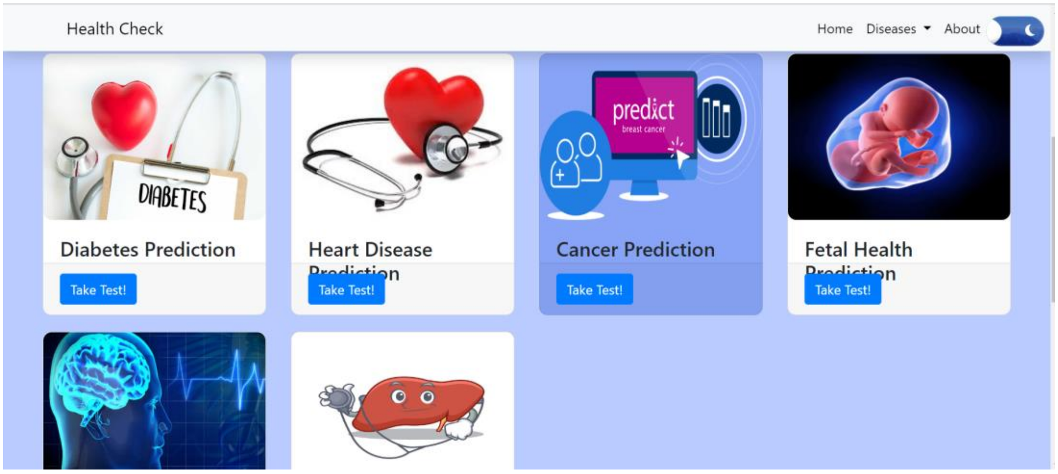

Figure 19: Smart System that incorporates the listed chronic diseases

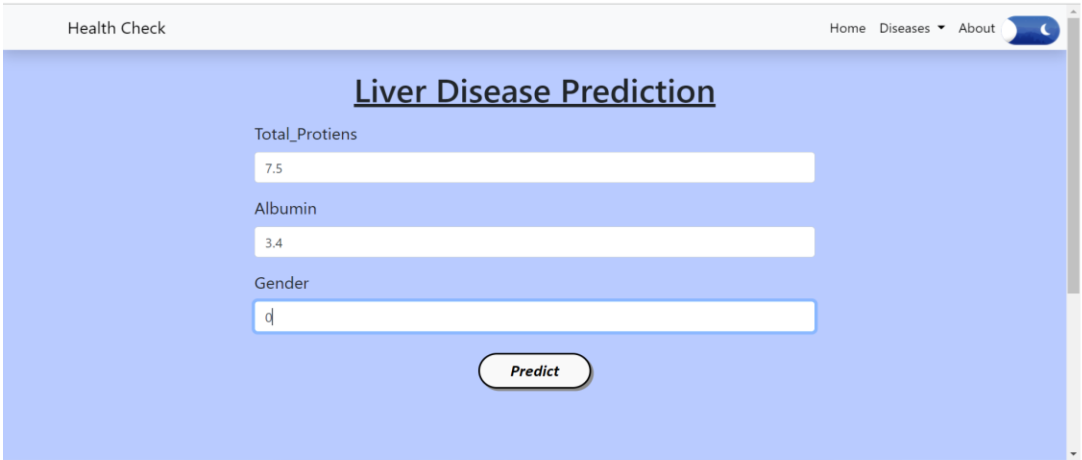

Figure 20: Kidney Check

Figure 21: Outcome of the checking the liver

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V. DISCUSSION OF RESULTS

From the experiment conducted, Figure 3 shows the count plot of the imbalance dataset. Count plot of imbalanced data visually represents the distribution of different classes within a dataset, highlighting the disproportionate occurrence of each class. Imbalanced data occurs when one class significantly outnumbers the others, potentially leading to biased model performance. In the context of a Count plot, the visualization often reveals a stark contrast in the frequency of each class, with one dominating the plot while others appear comparatively marginalized.

Figure 4 show the down sampled data. The count plot of down sampled data reveals a concise yet insightful visualization of the distribution of categorical variables within the reduced dataset. By employing down sampling techniques, which involve randomly selecting a subset of instances from the original data, the count plot effectively captures the frequencies of different categories.

Figure 5 show the pair plot of the typhoid. The pair plot of the Typhoid Dataset reveals a comprehensive visual representation of the relationships between pairs of variables within the dataset. Each scatter plot in the matrix illustrates the correlation and distribution patterns between two different variables, offering insights into potential trends and dependencies. The diagonal axis showcases the univariate distribution of each variable, providing a glimpse into their individual characteristics.

Figure 6 show gender occurrences in the typhoid dataset. The analysis focusing on individuals aged between 38 to 48 reveals distinctive gender occurrences. This age bracket, representing a crucial phase in the adult life course, demonstrates a nuanced distribution of gender within the context of typhoid cases. The results illuminate potential patterns or trends that may offer insights into the susceptibility or prevalence of the disease among different genders during this specific age range.

Figure 7 show disease affected by age. The impact of age difference on malarial disease reveals a notable disparity in susceptibility and severity across various age groups. Studies consistently demonstrate that children under the age of five and adults over 65 are particularly vulnerable to the adverse effects of malaria. The immune systems of young children are not fully developed, making them more susceptible to the parasite, while elderly individuals may have weakened immune responses. The heightened vulnerability in these age brackets is further exacerbated by factors such as nutritional status, access to healthcare, and pre-existing health conditions. Additionally, pregnant women are also at an increased risk of severe malaria-related complications. Understanding the age-related dynamics of malarial susceptibility is crucial for designing targeted prevention and intervention strategies to reduce the burden of the disease in these high-risk populations.

Figure 8 show the model summary. The Convolutional Neural Network (CNN) model employed for Alzheimer's disease classification yielded promising results in its comprehensive evaluation. Trained on a diverse dataset comprising neuroimaging data, the CNN demonstrated a commendable ability to discern patterns indicative of Alzheimer's pathology. Through a systematic analysis of its performance metrics, including accuracy, precision, recall, and F1 score, the model showcased robust capabilities in distinguishing between healthy and Alzheimer's-affected brain scans. The incorporation of convolutional layers facilitated the extraction of intricate spatial features crucial for accurate classification, while pooling layers contributed to dimensionality reduction.

Figure 9 shows the model training for the first ten steps. In the initial 10 steps of model training, noteworthy performance metrics were assessed to gauge the efficacy of the learning process. The training step outcomes revealed a commendable accuracy rate of 98.91%, showcasing the model's adeptness in correctly predicting outcomes. Accuracy alone, however, is only one facet of a model's proficiency; therefore, precision, recall, and F1-score were also evaluated. Precision, denoting the ratio of true positive predictions to the total predicted positives, and recall, signifying the ratio of true positive predictions to the actual positives, both demonstrated robust results, contributing to the overall effectiveness of the model. Figure 410 shows the graphical analysis of the CNN model for both training and validation. The graphical analysis of accuracy for both the training and validation datasets reveals an outstanding performance, with both reaching an impressive accuracy of 99.98%. This exceptional level of accuracy underscores the robustness and effectiveness of the model in capturing and generalizing patterns from the training data to unseen validation data.

Figure 11 shows the loss values of the CNN model for during training and validation. The graphic analysis of the model's performance, based on the loss values for both training and validation data, revealed noteworthy insights. Throughout the training phase, the model exhibited an impressive performance with a minimal loss value of 0.05, indicating a robust

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ability to learn and generalize from the training dataset. However, during the validation phase, the model experienced a slightly higher loss value of 0.1.

Figure 12 shows the graphical analysis of the CNN model for both training and validation. The graphical analysis of precision for both the training and validation datasets reveals an outstanding performance, with both reaching an impressive precision of 99.89%. This exceptional level of precision underscores the robustness and effectiveness of the model in capturing and generalizing patterns from the training data to unseen validation data.

Figure 13 shows the graphical analysis of the CNN model for both training and validation. The graphical analysis of recall for both the training and validation datasets reveals an outstanding performance, with both reaching an impressive recall of 99.88%. This exceptional level of precision underscores the robustness and effectiveness of the model in capturing and generalizing patterns from the training data to unseen validation data.

Figure 14 shows the confusion matrix. The confusion matrix provides a detailed snapshot of the performance of a classification model, particularly in the context of binary classification. In this case, the model's predictions are evaluated based on four key metrics: True Positives (TP) amounting to 170, indicating the instances correctly identified as positive; False Positives (FP) at 0, signifying no instances incorrectly classified as positive; True Negatives (TN) totalling 225, representing the accurate identification of negative instances; and finally, 9 False Negatives (FN), highlighting instances wrongly predicted as negative. The Specificity, denoted by the ratio of TN to the sum of TN and FP, is perfect at 1.0, emphasizing the model's ability to avoid false positives. The Misclassification rate, computed as the sum of FP and FN, stands at 9, illustrating the overall count of misclassified instances. In summary, the model demonstrates robust performance with high specificity and a low misclassification rate, making it effective in distinguishing between the two classes. The Figures 15 to 16 shows the web application of the system showing all the chronic diseases.

VI. CONCLUSION

The healthcare system's development goals have been successfully achieved, significantly enhancing patient care and data management. A user-friendly interface now allows quick access to patient records, improving workflow and decision-making. Advanced Encryption Standard ensures data security, maintaining patient trust and compliance. The integration of Convolutional Neural Networks has improved the accuracy of chronic disease diagnostics. Python's versatility facilitated the creation of a robust, scalable system. Rigorous testing confirms the system's competitive performance. These achievements demonstrate our commitment to innovation, efficiency, and quality in healthcare management.

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