**Rajarambapu Institute of Technology, Rajaramnagar**



**Department of Information Technology**

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***Capstone Project Synopsis***

| **Class** | Third Year |
| --- | --- |
| **Area of the Project** | Deep Learning & Cloud |
| **Title of the project** | Cloud-Based Chronic Disease Prediction Using Deep Learning Approach |
| **Project Guide Name** | Prof. Savita P. Patil |
| **Team Leader’s Name** | Pranav Avinash Desai |
| **Group Number** | 20 |

**Members**

| **Sr. No.** | **PRN** | **Name of the student** | **Email** | **Sign** |
| --- | --- | --- | --- | --- |
| 1 | 2210051 | Sakshi Rajendra Pawar | 2210051@ritindia.edu |  |
| 2 | 2210054 | Pranav Avinash Desai | 2210054@ritindia.edu |  |
| 3 | 2210003 | Ajinkya Vikram Bhosale | 2210003@ritindia.edu |  |

|  |  |  |
| --- | --- | --- |
| **Sign of Project Guide** | **Sign of Project In-charge** | **Sign of HOD, IT** |

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1. **Introduction**

Diabetes, heart disease, and kidney disease are among the chronic disorders that contribute the most to severe health outcomes, as well as mortality across the world. They have the potential to develop slowly over a long period, and when diagnosed late, can complicate the health status of an individual. Timely prediction and diagnosis are critical to preventing the progression of these diseases that can impact a person's quality of life and, in many cases, lead to premature death.

Machine Learning (ML) and Deep Learning (DL) are very useful in predicting and diagnosing chronic diseases by analyzing complex patterns in medical data. Deep Learning models such as Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), and Long Short-Term Memory (LSTM) improve prediction accuracy by recognizing different patterns within large medical datasets. By utilizing these methods, predictive healthcare systems can issue early alerts, allowing for timely medical interventions and tailored treatment plans.

Cloud computing is essential in contemporary healthcare applications, providing scalable, secure, and real-time data processing capabilities. A cloud-based system guarantees that patient data is stored and processed efficiently, making it accessible to healthcare professionals from any location, regardless of geographical barriers. Cloud platforms offer strong security measures to protect data privacy and ensure compliance with healthcare regulations.

This project seeks to solve these problems by building a cloud-based application that employs deep learning technology to predict chronic diseases using information from the patients and their previous health records.Because the system will be cloud based, it will be real-time, scalable, and available for use by clients from everywhere, which makes the application highly accessible and convenient to use. The deep learning model will be designed to improve the accuracy and reliability of disease predictions, allowing for earlier intervention and personalized healthcare solutions.

1. **Objectives:**
2. To prepare comprehensive dataset for chronic disease prediction.
3. To build a deep learning model for chronic disease prediction.
4. To develop a chronic disease prediction model on a cloud platform.
5. **Literature Survey**

This section presents the critical analysis of research papers focused on machine learning and deep learning based clinical decision support systems for chronic disease predictions.

C. T. Wu *et al.* [1] created a precision health service aimed at preventing and managing chronic diseases through the use of wearable devices, smartphone apps, AI-assisted telecare platforms, and environmental monitoring. To analyze the gathered data, the authors utilized a range of machine learning and deep learning techniques, including decision trees, random forests, AdaBoost, and Deep Neural Networks (DNNs).The study achieved an average accuracy of 88.46%, showcasing the effectiveness of AI in monitoring chronic diseases. One limitation noted in the study was the reliance on wearable devices and smartphone applications, which may hinder adoption among populations without access to such technologies.

M.A.Reshan *et al.* [2] introduced an innovative Ensemble Deep Learning (EDL) clinical decision support system aimed at predicting diabetes. This system integrates ANN, LSTM, and CNN models to deliver impressive accuracy. The research utilized three datasets: the Pima Indian Diabetes Dataset, the diabetes dataset from Frankfurt Hospital in Germany, and the Iraqi Diabetes Patient Dataset, resulting in an overall accuracy of 98.45%. The implementation was carried out using Scikit-learn, NumPy, Keras, and TensorFlow.

N. Bhaskar *et al.* [3] introduced an automated medical system designed to detect type 2 diabetes through a deep hybrid architecture. This model utilized a Convolutional Neural Network (CNN) alongside a Correlational Neural Network (CORNN) to analyze exhaled breath samples from individuals diagnosed with diabetes. The research highlighted the significance of non-invasive methods for diabetes detection. The model demonstrated impressive accuracy, showcasing the potential of breath analysis in medical diagnostics.

Both studies [2],[3] recognized that issues related to data quality, such as missing or incomplete medical records, could affect the reliability of the models. The combination of CNN, LSTM, and CORNN facilitated improved feature extraction and robust classification, enhancing the prediction and detection of diabetes. These studies played crucial role in advancing diabetes prediction and detection by utilizing deep learning techniques.

M. M. Ali *et al.* [4] proposed an IoT-based framework for detecting Chronic Kidney Disease (CKD) through a deep learning approach. The authors applied an Anova-F feature selection technique to identify the most relevant features for classification.The method utilized a Multi-layer Perceptron (MLP) classifier, achieving an impressive accuracy of 99%. Additionally, the research compared the performance of various classifiers, including Artificial Neural Networks (ANN), Recurrent Neural Networks (RNN), Gated Recurrent Units (GRU), and Support Vector Machines (SVM), demonstrating the superiority of their approach.

J. Chaki and A. Ucar [5] Automated kidney stone diagnosis is done efficiently and robustly as presented in paper by utilizing an inductive transfer ensemble based Deep Neural Network (DNN) model. The study was based on the analysis of Computed Tomography (CT) images of kidney stones and utilized datasets including KD, KD1, KD2, and KD3 which were gathered by the Picture Archiving and Communication System (PACS). The system was able to achieve accuracy rates of 99.8% and 96.7%.

K. Venkatrao and S. Kareemulla [6] presented HDLNET, a hybrid deep learning network model that incorporates intelligent IoMT (Internet of Medical Things) for detecting and classifying Chronic Kidney Disease (CKD). The research introduced the Deep Separable Convolution Neural Network (DSCNN), which was optimized using the Sooty Tern Optimization Algorithm. By utilizing the Chronic Kidney Disease (CKD) dataset, the model achieved an impressive accuracy of 99.18%, showcasing its effectiveness in the early detection of CKD.

S. M. M. Elkholy, et al. [7] developed an intelligent classification and prediction model for Chronic Kidney Disease (CKD) detection at an early stage using a modified Deep Belief Network (DBN). The research utilized UCI Chronic Kidney Disease (CKD) Dataset and had a prediction accuracy of 98.50%. The study was done in MATLAB, and a wide range of variables were extracted that included patient demographics, biochemical, and clinical features like age, blood pressure, specific gravity, albumin, sugar, red blood cells, pus cells, hemoglobin etc.

G. Chen et al. [8] introduced an Adaptive Hybridized Deep Convolutional Neural Network (AHDCNN) aimed at the early detection of Chronic Kidney Disease (CKD) within the Internet of Medical Things (IoMT) framework. The research evaluated the performance of different deep learning methods and used sample datasets sourced from the DeepLesion repository (https://nihcc.app.box.com/v/DeepLesion). The model reached an FI-Score of 97.3%, demonstrating its strong predictive abilities.

The above studies commonly faced limitations such as constraints on dataset size, regulatory and privacy issues, noise in medical data, and challenges with integration. Despite these hurdles, the proposed algorithms showed impressive predictive accuracy, robustness, and efficiency in detecting Chronic Kidney Disease (CKD), positioning them as valuable tools for early diagnosis and intervention in healthcare environments.

M. Golec *et al.* [9] introduced an innovative healthcare framework powered by AI, which leverages the Internet of Things (IoT) and a serverless computing environment to tackle the issue of heart disease-related deaths. The dataset for this research was obtained from the UCI ML Repository and used in the LightGBM model implemented on Google Cloud Platform (GCP) Cloud Functions. The system achieved an impressive prediction accuracy of 91.80%, showcasing its effectiveness in detecting heart disease.

The study presented by S. S. Sarmah [10] introduced an innovative IoT-based system for monitoring patients and predicting heart disease, utilizing a Deep Learning Modified Neural Network (DLMNN). This system verified heart patients from designated hospitals and uses wearable IoT sensor devices affixed to the patient's body to send real-time health information to the cloud for analysis. By leveraging the Hungarian Heart Disease Dataset, the model achieved an impressive accuracy of 98.25% based on a dataset of 500 records. This research highlights the significant potential of IoT-enabled AI systems in enhancing patient monitoring and decision-making in cardiac care.

A. A. Almazroi et al. [11] presented a Clinical Decision Support System (CDSS) built on deep learning techniques for heart disease prognosis. The research employs both DNN and CNN algorithms which use the Hungarian Heart Disease Dataset. The model achieves 83% prediction accuracy and shows improved overall accuracy, sensitivity, and specificity as compared to single models and other ensemble approaches. This work shows promise while predicting there is room for improvement in heart disease patient data image analysis.

Y. Pan et al. [12] presented an Enhanced Deep Learning Assisted Convolutional Neural Network (EDCNN) system that operates on the Internet of Medical Things (IoMT) platform for predicting heart disease. This system acts as a decision support tool, allowing doctors to effectively diagnose heart-related issues through globally accessible cloud-based platforms. The research utilized the Hungarian Heart Disease Dataset and integrated various deep learning models, such as ANN, DNN, RNN, and EDCNN, achieving an impressive accuracy rate of 99.1%. The key patient features analyzed included age, sex, type of chest pain, resting blood pressure, cholesterol levels, blood sugar, maximum heart rate, exercise levels, OldPeak, and the target variable.

S. N. Ali et al. [13] presented an end-to-end deep learning framework aimed at real-time denoising of heart sounds (phonocardiograms, PCGs) to improve the detection of cardiac diseases in noisy settings. The research employed Bi-LSTM (Bidirectional Long Short-Term Memory) networks and assessed performance using the PASCAL Heart Sound dataset along with the 2016 PhysioNet/CinC Heart Sound (PHS) dataset. This framework tackled the challenge of environmental and physiological noise that can distort heart sound signals recorded with digital stethoscopes, potentially affecting their important and critical features.

A common limitation noted in these studies was the absence of adequate security and privacy measures, which could compromise the protection of patient data. The deep learning models used in these studies offered notable benefits compared to traditional machine learning methods. For example, LightGBM and DLMNN showed remarkable efficiency in managing large datasets while still achieving high prediction accuracy.

Chakraborty and Kishor [14] proposed a real time, cloud-based monitoring system, which uses computational health systems to predict heart disease. Their study utilized a range of machine learning classification algorithms, such as K-Nearest Neighbors (K-NN), Support Vector Machine (SVM), Random Forest (RF), and Artificial Neural Networks (ANN). The dataset for this research was collected through the Internet of Medical Things (IoMT) and focused on essential health indicators like temperature, heart rate, blood pressure, blood sugar, and blood oxygen levels.

M. A. Khan and F. Algarni [15] proposed a Healthcare Monitoring System for Diagnosing Heart Disease in the IoMT Cloud Environment Using Modified Salp Swarm Pptimization (MSSO) and Adaptive Neuro-Fzzy Inference System (ANFIS) introduced a framework based on the Internet of Medical Things (IoMT). The system was trained using the Hungarian Heart Disease Dataset and the Framingham Heart Disease Dataset, achieving an impressive accuracy rate of 99.45%.The study emphasized the advantages of MSSO in both exploration and exploitation, while also noting its limitations, such as slow and premature convergence.

Cloud computing significantly contributed to these studies [14],[15] by offering a flexible infrastructure for handling and storing vast amounts of health data. It facilitated real-time access, remote monitoring, and effective computational analysis, leading to improved prediction accuracy. By incorporating cloud-based IoMT systems, healthcare professionals were able to improve early diagnosis and intervention, ultimately lowering mortality rates associated with heart disease.

A. Sundas et al. [17] created a machine learning-based model for predicting Chronic Kidney Disease (CKD), which is integrated with a user-friendly web application. They employed various machine learning algorithms, including K-Nearest Neighbors (KNN), Artificial Neural Networks (ANN), and Support Vector Machines (SVM), to detect CKD. The model was trained on a dataset that included several clinical parameters such as age, blood pressure, random blood glucose levels, hemoglobin, serum creatinine, and other relevant biomarkers for kidney health. To ensure easy access and real-time predictions, the authors utilized the Flask framework to develop the web application.

R. K. Haldera et al. [18] introduced a Smart Patient Monitoring and Recommendation (SPMR) framework that utilizes deep learning and cloud-based analytics for managing chronic diseases. This framework focuses on monitoring patients with chronic blood pressure issues, employing Multi-Layer Perceptron (MLP), Convolutional Neural Networks (CNN), and Recurrent Neural Networks (RNN). The research used a dataset on Chronic Blood Pressure Disorders collected through Ambient Assisted Living (AAL) devices. The system achieved impressive accuracy (99.96%) and an F1-score between 0.91 and 0.97.

The limitation across these studies was the narrow application of the models to specific diseases, highlighting the need for broader validation across various chronic conditions. Additionally, there was a risk of overfitting, which could be addressed through hyperparameter tuning and regularization techniques. The findings indicated that deep learning models, especially CNN and RNN, excelled in feature extraction, while traditional machine learning algorithms like SVM and KNN were effective for classification with lower computational demands.

A. A. Ali Tabtaba and Oguz Ata [19] introduced a new model for detecting Diabetic Retinopathy (DR) that utilizes a hybrid heuristic-aided deep learning approach. They collected and pre-processed fundus images before inputting them into a Hybrid Cascaded Multi-scale Deep Convolutional Neural Network (HCMD-CNN). This model combined Region Attention Networks (RAN) and MobileNet to effectively extract features. The training and evaluation were conducted using the IDRiD dataset, and the model achieved an accuracy of 91%.

R. O. Ornelasa *et al.* [20] proposed the use of MobileNetV2 was investigated for the early detection of lung cancer through a thorough transfer learning approach. This model was able to classify Lung Adenocarcinoma (LAC), Benign Lung Tissue (BLT), and Lung Squamous cell Carcinoma (LUSC) using the LC25000 dataset. To enhance generalization, additional histopathological images from the National Cancer Institute were included. The model reached a high classification accuracy of 98.77%. Despite this impressive accuracy, the study acknowledged limitations, including issues with dataset.

There are some limitations pointed in both studies, Diabetic Retinopathy (DR) detection model had trouble with optimal feature extraction, while the lung cancer detection model encountered difficulties due to an imbalanced dataset. Nevertheless, the studies showcased the benefits of employing deep learning-based models like MobileNet and HCMD-CNN, which offered high accuracy and efficient computation for analyzing medical images.

1. **Problem Statement**

The project aims to develop a cloud-based deep learning system that predicts chronic diseases, enhancing early diagnosis and personalized healthcare interventions.

1. **Problem Description**

Chronic diseases like diabetes, heart disease, and kidney disease have surfaced as major health problems across the globe, affecting countless individuals and acting as a significant burden for healthcare systems. For proper management of these diseases, early detection is necessary and highly accurate prediction is important. Unfortunately, most conventional methods of diagnosis are expensive, time-consuming and out of the grasp of a general practitioner, especially in rural and third world countries.

As technology continues to advance rapidly, there is an increasing demand for a smart, cloud-based solution that utilizes deep learning methods to analyze patient data and deliver precise predictions for chronic diseases. Current systems frequently face challenges like limited scalability, inefficiencies in managing large datasets, and a lack of real-time insights for healthcare professionals and patients.

To tackle these challenges, our project aims to create a cloud-based system for predicting chronic diseases. This system will leverage advanced machine learning algorithms to examine patient health records, lifestyle choices, and medical history, allowing us to forecast the risk of developing chronic conditions. This will enable healthcare providers to make well-informed decisions, improve patient outcomes, and reduce the overall pressure on healthcare resources.

1. **Problem Solution**

The proposed project focuses on creating a cloud-based deep learning system designed for the early prediction of chronic diseases, including diabetes, kidney disease, and heart disease. By utilizing advanced machine learning and deep learning techniques, this system will analyze patient data to facilitate early intervention and enhance healthcare outcomes. The cloud-based architecture guarantees accessibility, scalability, and real-time data processing.

Key features of the solution include:

**Data Collection and Storage**: Patient health records, lifestyle information, and clinical data will be securely stored in cloud storage solutions like Google Cloud Storage or Amazon S3.

**Preprocessing and Feature Engineering:** Techniques for data cleaning, normalization, and transformation will ensure that the input for model training is of high quality.

**Deep Learning Models:** Advanced neural networks, including DNN, CNN, and LSTM, will be employed to accurately detect patterns and classify disease risks.

**Cloud-Based Deployment:** The model will be deployed on a cloud platform, allowing for real-time disease predictions accessible through web or mobile applications.

**Security and Compliance:** Cloud security measures, such as data encryption, access control, and adherence to healthcare regulations, will ensure the privacy of patient data.

1. **System Architecture**

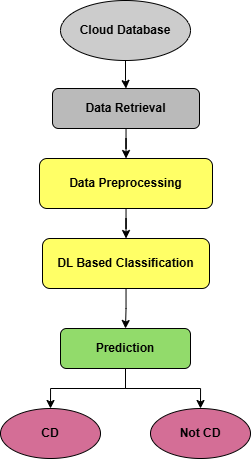
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Fig.7.1 System Architecture

1. **Methodology**
   1. **Dataset Retrieval from Cloud:**

To ensure accurate predictions, use of a well researched dataset is very important. Dataset will be used are Pima Indians Diabetes Dataset (UCI Machine Learning Repository), Chronic Kidney Disease (CKD) Dataset (UCI Machine Learning Repository), Heart Disease Dataset (Hungarian Heart Disease Dataset from UCI Repository).These datasets are stored in cloud repositories such as AWS S3 to guarantee scalability and accessibility.

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* 1. **Data Preprocessing:**

To achieve high-quality inputs for model training, it is crucial to preprocess the datasets stored in the cloud, which contain missing values and multivariable attributes. So we can use different methods i.e Addressing Missing Values, Feature Scaling, Normalization, Eliminating Duplicates & Irrelevant Features. By applying these preprocessing techniques, we ensure that the all dataset is clean, well-organized, and ready for deep learning-based chronic disease prediction.

* 1. **Deep Learning Model Development:**

For chronic disease prediction, deep learning algorithm such as Deep Neural Networks (DNN), Convolutional Neural Networks (CNN), and efficient models like LightGBM and MobileNet will be used. These models will be trained on the preprocessed datasets stored in the cloud and assess their performance using metrics such as accuracy, precision, recall, and F1-score.

* 1. **System Integration:**

Connect the model with an intuitive interface designed for healthcare professionals. Guarantee data privacy and adherence to healthcare regulations.

1. **Modules**
   1. **Dataset Retrieval from Cloud**

This module offers a representative and varied dataset that is prepared for predictive modeling and contains disease labels and health characteristics.

To achieve scalability, accessibility, and security, the datasets are stored in a cloud storage service such as:

* Amazon S3 (AWS) – A dependable cloud storage option for handling large datasets.

When a dataset request is made, the module retrieves the data from the cloud. Each dataset includes specific attributes related to the diseases as mentioned below:

* Diabetes Dataset :
  + Features:Pregnancies,Glucose level, Blood Pressure, Insulin, BMI, Age,, Skin Thickness, Diabetes Pedigree Function
  + Target Label: Outcome (0 = No Diabetes, 1 = Diabetes)
  + No. of records : 768
* Kidney Disease Dataset :
  + Features: Blood Urea, Serum Creatinine, Hemoglobin, Blood Glucose Random, Blood Pressure, Sodium, Potassium, Red Blood Cells, Specific Gravity, Albumin
  + Target Label: Outcome (CKD/Not CKD)
  + No. of records : 400
* Heart Disease Dataset :
  + Features: Age, Sex, Chest Pain Type, Resting Blood Pressure, Cholesterol, Fasting Blood Sugar, Resting ECG, Max Heart Rate.
  + Target Label: Outcome (0 = No Heart Disease, 1 = Heart Disease)
  + No. of records : 1190
  1. **Data Preprocessing Module**

Based on the input health data, this module generates a trained neural network that can precisely forecast the likelihood of chronic diseases.

* Handling Missing Values (Imputation Techniques) :

Real-world datasets frequently have missing or incomplete data. There are several methods to address missing values: Mean/Median Imputation, Mode Imputation, K-Nearest Neighbors (KNN) Imputation, Forward/Backward Fill.

* Feature Scaling (Normalization or Standardization) :

Machine learning models perform better when numerical values are on a similar scale.eg. Min-Max Scaling, Standardization (Z-score Normalization)

* Removing Duplicate or Irrelevant Features :

If a patient's data is recorded more than once, it is eliminated to prevent bias.

* 1. **Deep Learning Module**

The Deep Learning Module focuses on training a neural network using a preprocessed dataset to assess the likelihood of chronic diseases such as Diabetes, Kidney Disease, and Heart Disease. The model evaluates whether a patient has a disease based on specific health attributes.

Deep Learning Models :

We utilize various deep learning models with different architectures to improve prediction accuracy and efficiency.

A) Deep Neural Network (DNN) – Tabular Medical Datasets

B) Convolutional Neural Network (CNN) – Image-Based Data

C) Lightweight Deep Learning Models for Efficiency

To ensure quick processing with minimal computational resources, we implement lightweight deep learning models:

* LightGBM (Light Gradient Boosting Machine)
* MobileNet
* EfficientNet
  1. **Evaluation Module**

To ensure the effectiveness of the deep learning model in predicting chronic diseases, it will be evaluated using several performance metrics.

Performance Metrics:

* Accuracy – Measures the overall correctness of the predictions.
* Precision – Looks at how many of the predicted positive cases were actually positive.
* Recall (Sensitivity) – Assesses the model's capability to identify true positive cases.
* F1-Score – Balances precision and recall for a more thorough evaluation.

1. **System requirements with justification**
   1. Software requirements

* Python (for deep learning model development)
* AWS Cloud platform
  1. Hardware requirements
* RAM (minimum : 8GB , recommended : 16 GB or higher).
* Processor (minimum : intel i5/ AMD Ryzen 5, recommended : i7/Ryzen 7 or higher).

1. **Expected Outcomes**
   1. **Enhanced Prediction Accuracy**: Advanced early detection of chronic diseases through deep learning models.
   2. **Cloud-Based Accessibility:** A scalable, real-time disease prediction system that can be accessed from any location.
   3. **Healthcare Efficiency:** Decreased diagnostic time and costs, benefiting both healthcare professionals and patients.
   4. **Prototype Development:** A working cloud-based application for chronic disease prediction, laying the groundwork for future improvements and real-world implementation.
2. **Challenges & Limitations**
   1. **Real Time Data Availability**: To train accurate models, access to real time data is crucial, obtaining real-time medical data can be difficult due to restrictions on data access and inconsistencies in record-keeping.
   2. **Computational Costs**: Deep learning models demand significant computational resources, which can lead to high expenses when utilized on cloud platforms.
   3. **Privacy Concerns**: The management of sensitive patient information raises privacy issues, necessitating strong security measures.
   4. **Data Ownership & Accessibility:** Organizations and individuals that possess medical datasets may impose limitations on their use, which can restrict access to vital data needed for training and testing predictive models.
3. **Conclusion and Future Scope**

This project introduces a cloud-based deep learning method for predicting chronic diseases, providing an innovative and scalable solution for early diagnosis and personalized treatment. By combining deep learning with cloud computing, the system facilitates real-time analysis of patient data, enabling prompt medical intervention.

Future improvements to this project could involve:

**Integration with IoT Devices:** Adding real-time health monitoring through wearable technology.

**Use Image Data for Training Model:** Alongside structured medical records, integrating medical imaging datasets (like MRI, CT scans, and X-rays) can boost the accuracy of disease predictions.

**Improved Model Optimization:** Employing hyperparameter tuning methods, such as Grid Search and Random Search, along with advanced deep learning architectures, will enhance model efficiency and accuracy.

By focusing on these areas, the system can evolve into a vital resource for healthcare professionals, enhancing patient outcomes and alleviating the strain on medical institutions.

1. **Project Outcome**

* Research Paper publication.
* Participations in national hackathons.
* A cloud-based application for chronic disease prediction.

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