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Kidney Disease Prediction with Encrypted Data Sharing in Healthcare

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Abstract: *A vital component of contemporary healthcare is disease risk assessment, which makes it possible to estimate a person's propensity to develop particular medical problems. Analyzing a variety of risk factors, including age, gender, lifestyle decisions, past medical history, and genetic susceptibility, is part of this procedure. The ability to access vast healthcare datasets and the development of sophisticated machine learning algorithms have greatly increased the accuracy of illness risk prediction. Using machine learning techniques, this proposed strategy offers an outline of the methodology involved in kidney disease prediction. Kidney disease Prediction seeks to enable early detection and intervention by utilizing machine learning (ML) techniques, such as Support Vector Machines (SVM), to predict the risk of kidney disease based on user query data. The project intends to increase treatment efficiency, improve quality of life for those at risk of renal disease, and expedite healthcare delivery through the integration of an appointment booking system and secure exchange of prescriptions and ideas. Utilizing the findings of the disease risk assessment, customized preventative plans are created based on the risk profile of the individual. These tactics could involve genetic counselling, specialized screening techniques, lifestyle adjustments, or preventative medicine. In order to keep models current with the most recent developments in medicine and data patterns, they must be continuously monitored and adjusted*

Keywords: Dataset Collection, Preprocessing, Model Build, Query Data, Support Vector Machine, Disease Classification, Appointment Booking, Prescription Data, Advanced Encryption Standard, Secure Data Sharing

I. INTRODUCTION

Disease risk assessment, which entails projecting a person's probability of contracting a specific disease, is a crucial responsibility in the healthcare industry. Analysing a variety of risk factors, including age, gender, lifestyle, medical history, and genetic susceptibility, can help achieve this. Accurately predicting illness risk and creating individualized preventative interventions are made possible by massive healthcare databases and sophisticated machine learning algorithms. Utilizing a dataset, the process of assessing the risk of a disease entails gathering and preprocessing data from a variety of sources, including genetic, medical imaging, and electronic health records. Next, machine learning methods like logistic regression, decision trees, random forests, and neural networks are used to examine this data. Accurate disease risk assessment is made possible by these algorithms' ability to recognize patterns and connections between different risk factors and disease outcomes. The outcomes of a disease risk assessment can be utilized to create individualized preventative plans that include dietary adjustments, early detection, and focused medical treatments. This can enhance people's health outcomes and lessen the overall burden of disease. All things considered, illness risk assessment utilizing datasets and machine learning algorithms has the potential to transform the healthcare industry and allow tailored preventive measures that can enhance patient outcomes and lower medical expenses.

- **Data collection:** Collect a dataset of symptoms and diseases that includes various symptoms associated with each disease.
- **Data preprocessing:** Pre-process the dataset by removing any missing or irrelevant data, encoding categorical variables, and scaling the numerical data.

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- **Feature selection:** Identify the most important features that contribute to the prediction of the disease. This can be done using feature selection algorithms such as Recursive Feature Elimination (RFE) or Principal Component Analysis (PCA).
- **Train/test split**: Split the dataset into training and testing sets. The training set will be used to train the SVM algorithm, while the testing set will be used to evaluate its performance.
- **Model training:** Train the SVM algorithm on the disease training data.
- **Model evaluation:** Evaluate the performance of the model on the disease testing data. This approach ensures that patient privacy is protected while still allowing accurate disease prediction using machine learning algorithms.

1.1 Machine Learning

Artificial intelligence (AI) machine learning allows systems to automatically learn from experience and get better at it without needing to be explicitly designed. The creation of computer programs that can access data and utilize it to learn for themselves is the main goal of machine learning. In order to find patterns in data and use the examples we provide to guide future decisions, learning starts with observations or data, such as examples, first-hand experience, or instruction.

Machine learning is utilized in a variety of AI applications, including recommender systems, driverless cars, picture and speech recognition, natural language processing, and more. Large-scale data processing, pattern and relationship recognition, and decision-making based on learned information are all necessary for these applications. Other subfields of artificial intelligence (AI) include robotics, expert systems, knowledge representation, planning, and reasoning in addition to machine learning. Although each of these subfields focuses on a distinct facet of AI, they are all connected and can cooperate to develop increasingly sophisticated AI systems.

All things considered, machine learning is a vital part of artificial intelligence (AI) and is responsible for helping computers learn and become more efficient at a variety of activities. Machine learning will probably remain a key component in allowing computers to develop intelligence beyond that of humans as artificial intelligence (AI) develops.

1.2 Some Machine Learning Methods

Algorithms for machine learning are frequently divided into supervised and unsupervised categories. For supervised algorithms to function properly, input and desired output must be provided, and feedback regarding the precision of predictions made during algorithm training must be provided by a machine learning-trained data scientist or analyst. Data scientists choose which features, or variables, to include in the model's analysis and prediction-making process. The algorithm will apply the knowledge it has gained to fresh data after training is finished. Data pertaining to intended outcomes can be used to train unsupervised algorithms. Instead, they analyze data and draw conclusions through an iterative process known as deep learning. For more sophisticated processing tasks than supervised learning systems, such as image recognition, speech-to-text, and natural language production, unsupervised learning algorithms, sometimes known as neural networks, are employed. These neural networks function by automatically sifting through millions of training data instances to find frequently subtle relationships between a large numbers of variables. The algorithm can comprehend fresh data by using its bank of associations once it has been trained. Because these algorithms need enormous volumes of training data, they are only practical in the big data era.

Machine learning algorithms are often categorized as supervised or unsupervised.

Supervised machine learning algorithms can apply what has been learned in the past to new data using labeled examples to predict future events. In order to forecast the output values, the learning algorithm generates an inferred function by analyzing a known training dataset. After enough training, the system can provide targets for any new input. Additionally, the learning algorithm has the ability to compare its output with the intended, correct result in order to identify faults and adjust the model as necessary.

In contrast, **unsupervised machine learning algorithms** are used when the information used to train is neither classified nor labeled. Unsupervised learning investigates how unlabeled data can be used by systems to infer a function that describes a hidden structure. The system analyzes the data and can make inferences from datasets to characterize hidden structures from unlabeled data, even when it is unable to determine the correct output.

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Semi-supervised machine learning algorithms fall somewhere in between supervised and unsupervised learning, since they use both labeled and unlabeled data for training – typically a small amount of labeled data and a large amount of unlabeled data. Systems that employ this technique can significantly increase the accuracy of their learning. Semi-supervised learning is typically used when training or learning from the collected labeled data involves the use of knowledgeable and pertinent resources. Otherwise, more resources are typically not needed to obtain unlabeled data.

Reinforcement machine learning algorithms is a learning method that interacts with its environment by producing actions and discovers errors or rewards. The two aspects of reinforcement learning that are most pertinent are trial-and-error search and delayed reward. By using this technique, machines and software agents may automatically figure out what the best course of action is in a given situation to optimize their performance. The agent must get basic reward feedback in order to determine the optimal course of action; this is referred to as the reinforcement signal.

Large-scale data analysis is made possible by machine learning. It may also take more time and resources to train it correctly, even though it typically produces faster, more accurate results to detect profitable possibilities or risky hazards. Machine learning can analyze vast amounts of information even more efficiently when combined with AI and cognitive technologies.

II. RELATED WORK

Santosh Kumar, et.al,…[1] Several tasks, including feature normalization, feature selection, and feature categorization, are included in this proposed study. For feature selection, we used principal component analysis (PCA), and for classification, we used extreme learning machine (ELM). In conclusion, a cloud computing infrastructure featuring three virtual machines (vCPU-4, vCPU-8, and vCPU-16) is employed to identify diabetes. The suggested model's effectiveness was assessed using the PIMA dataset in both standalone and cloud environments. Using the virtual machine vCPU-16, it achieved 90.57 percent accuracy, 82.24% sensitivity, 73.23% specificity, and 75.03% F-1 score. According to the experimental findings, the suggested model is better than other cutting-edge models with less characteristics and higher classification accuracy. Pre-processing, feature selection, and cloud-based categorization comprise the three phases of the proposed system. The primary feature matrices have been adjusted so that the variance is one and the mean is zero before the feature reduction stage. The feature selection process uses the PCA approach. The classification work has been carried out by the extreme learning machine (ELM).

Kommuri Venkatrao, et.al,…[2] A brand-new hybrid deep learning network model (HDLNet) for CKD early detection and prediction is presented in this suggested study. This study suggests the Deep Separable Convolution Neural Network (DSCNN), a deep learning-based method, for the early identification of CKD. The Capsule Network (CapsNet) extracts more processing qualities of characteristics selected to signal a kidney problem. To expedite the classification process, the relevant criteria are chosen via the Aquila Optimization Algorithm (AO) technique. Then, with less computational work, required features increase classification efficacy. CKD and non-CKD renal sickness are diagnosed with the DSCNN technique by the use of the Sooty Tern Optimization Algorithm (STOA).The dataset is then tested using the CKD dataset, which can be available in the UCI machine learning repository. The performance measures for the proposed CKD classification technique are specificity, sensitivity, MCC, PPV, FPR, and FNR. Further experimental results show that compared to the current state-of-the-art method, the proposed method produces a better categorization of CKD. The results and conclusions of the experiment are reported in the section that follows. This study uses a CKD dataset to validate the efficacy of the proposed method. There are two sets of data samples produced, the training dataset being one of them. Next, the testing dataset is used to evaluate the classifier.

Linta Antony, et.al,[3] Patients now have to wait longer to receive a diagnosis as a result of this. Accordingly, this research suggests that creating an intelligent system to categorize patients into CKD or non-CKD groups can assist medical professionals in managing a larger patient load and delivering diagnoses more quickly. Organizations can eventually deploy the suggested machine learning architecture in regional clinics with lower rates of medical expert retention, enabling patients in those places to receive early diagnoses. Few studies have employed unsupervised machine learning algorithms to far, despite the fact that numerous academics have attempted to address the issue by creating intelligent systems utilizing supervised machine learning techniques. This study's main goal is to apply different unsupervised algorithms, evaluate their performance, and determine the ideal combinations for optimum accuracy and detection rate. Vet unsupervised algorithms, K-Means Clustering, DB-Scan, I-Forest, and Auto encoder have all been used in this study. And combining them with different techniques for feature selection. The clinical data of CKD and non-CKD may be classified with an overall accuracy of 99% by integrating feature reduction techniques with the K-Means Clustering algorithm.

Shynu, et.al,[4] provides a practical privacy-preserving plan for patient health data gathered from Internet of Things (IoT) devices for the purpose of predicting sickness in the contemporary health care system (HCS). After the first authentication stage, the suggested system uses Log of Round value-based Elliptic Curve Cryptography (LR-ECC) to increase the security level during data transfer. On the hospital side, the patient data can be safely downloaded by authorized healthcare personnel. EHGA-DLNN, a Deep Learning Neural Network based on Herding Genetic Algorithm, may test this data using the trained system to predict the diseases. The experimental findings show that, in comparison to the current techniques, the suggested strategy enhances prediction accuracy, privacy, and security. The use of IoT technologies in the current healthcare application environment facilitates patient and physician application in the health domain. A proactive assessment of one's health can reduce the risk of many diseases. However, using the patients' medical records and disease information raises privacy concerns. Delays in treatment progress might give rise to privacy and security concerns about medical data, perhaps putting the patient's life in danger. As a result, getting a safe illness forecast without worrying about the accuracy of the data becomes a difficult task.

Pooja Yadav,et.al,[5] the dataset was balanced using the Synthetic Minority Over-Sampling Technique (SMOTE) algorithm. Boruta has also been investigated as a feature selection technique. We have presented an enhanced method that combines the Grid Search method with the Grey Wolf Optimization algorithm to tune hyper-parameters of various algorithms. The Grid Search approach necessitates a lot of searching, whereas the Grey Wolf Optimization technique is very precise, quickly searchable, and simply connected.

In this work, nine traditional classification approaches have been assessed. The Stacking Classifier is the focus of this study in order to evaluate the effectiveness of the prediction model that yields the best outcomes. 98.84% on the PIMA dataset, 98% on the Synthetic dataset after validation, 97.3% on the ADRC dataset, and 96.20% on the FHD dataset were the maximum F1-Scores achieved by the proposed model. To our knowledge, these two datasets and this kind of technique have not been the subject of any prior research. The suggested approach outperforms the others, according on the results of the comparison experiment conducted on the PIMA dataset. The proposed model's interpretation is also provided by this study. In order to determine what explain ability means for the application of machine learning models in clinical practice, it undertakes an ethical assessment.

III. BACKGROUND OF THE WORK

An effective and private-preserving online disease risk assessment system using multiple-outsourced vertical datasets is now healthcare provider to safely train a disease risk prediction model using vertically dispersed medical data from several medical centers and offer users privacy-preserving disease risk prediction services. Users' private information as well as that of medical facilities and e-healthcare providers can be securely protected throughout the process. First, it successfully trains a model for disease risk prediction using vertically dispersed data, and it allows for dynamic model updates. Under this approach, the e-healthcare provider can also effectively train the illness risk prediction model, even if medical centers collect various attributes from examples.

Second, it offers privacy preservation for both illness risk prediction and model training. Provide a modified Paillier cryptosystem for this application so that the prediction model may be safely trained without revealing private information about medical facilities. Additionally, the random masking technique is used in disease risk prediction, maintaining user queries and results as well as the e-healthcare provider's disease risk prediction model. The current system has an automated eHealth cloud system in place for early diabetes detection, which lowers the death rate and gives remote residents access to medical facilities.

One kind of Artificial Neural Network (ANN) that shows great promise for addressing classification problems is the Extreme Learning Machine (ELM). Several tasks, including feature normalization, feature selection, and feature classification, make up this research project. Extreme Learning Machine (ELM) was utilized for classification and Principal Component Analysis (PCA) for feature selection.

IV. PROPOSED SYSTEM MODEL

A number of critical measures must be taken during the creation of a disease risk prediction system for renal illness in order to guarantee the system's efficacy, privacy, and usability for a wide range of user groups. Using kidney disease-based dataset classification, disease risk assessment entails gathering data to create a model that can estimate a person's chance of contracting a specific illness. Three different user types make up the system: E-Healthcare systems, medical centers/hospitals, and patients/doctors. In the beginning, the system gathers and preprocesses medical records from the past related to kidney illness, including a range of patient characteristics and pertinent health markers. Put into practice the remote disease prediction and disease model training components of the disease risk prediction system. More specifically, we employ the Support Vector Machine approach to train the illness model using previous medical data obtained from confirmed patients.

Taking care of missing data and standardizing the format for analysis are part of preprocessing. The gathered data is then used to train a Support Vector Machine (SVM) algorithm, which forecasts the probability of developing renal disease. Strict precautions are taken during these procedures to protect the privacy and confidentiality of private medical data. To protect data integrity and stop unwanted access, encryption techniques including differential privacy and AES (Advanced Encryption Standard) encryption are implemented.

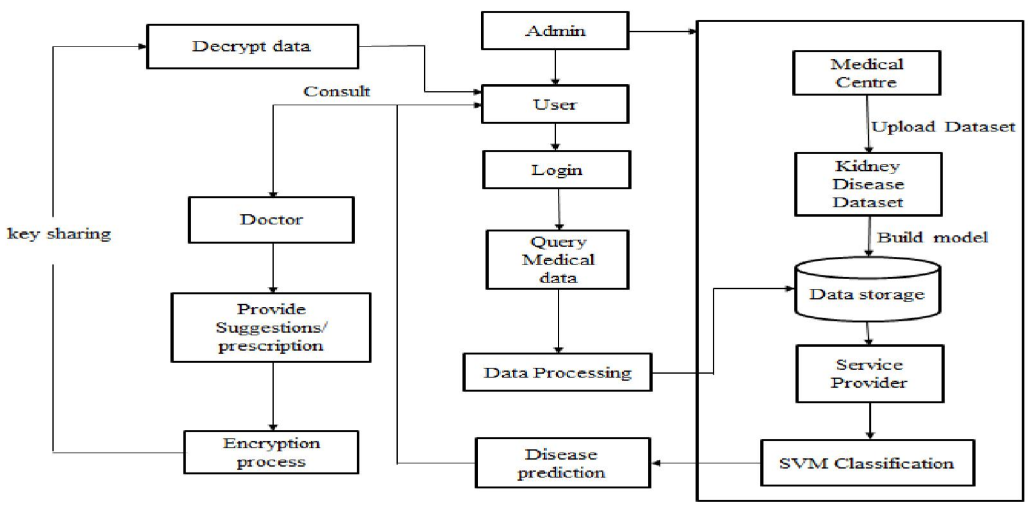

Fig.1 Proposed System Model

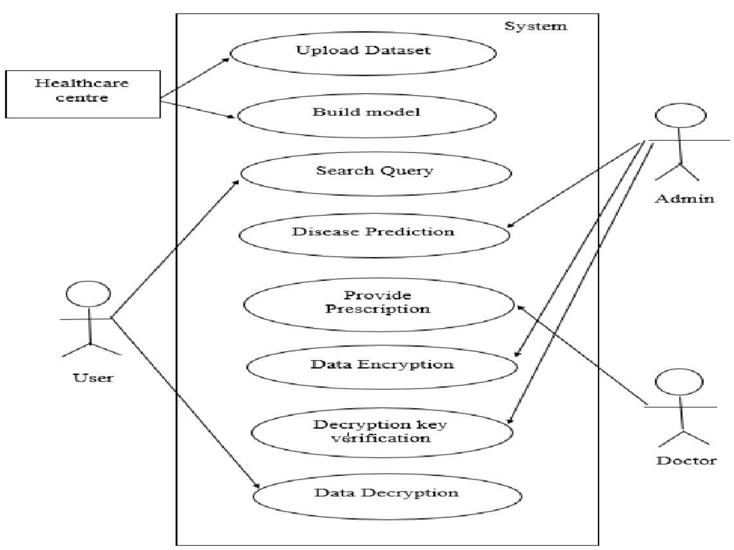

Fig.2 Usecase Model

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Admin

The disease risk prediction system's administrative center, the Admin Module, is in charge of user administration and system setup. The system administrator verifies the service platform's capabilities, or its ability to deliver efficient services. The system will share the secret key with the user for secure service access once the administrator has reviewed and approved the newly registered details. Administrators can adjust system parameters, set up encryption keys, and implement data privacy policies using user-friendly interfaces. The Admin Module protects the integrity of the disease risk prediction system and guarantees smooth operation by centralizing user administration and system setup.

Dataset Processing

The Dataset Processing Module, which is at the center of the disease risk prediction system, is in charge of carefully managing renal disease-related medical data. This module coordinates the gathering, cleansing, and archiving of various patient data to make sure it is appropriate for examination. Gather a dataset of medical records related to kidney illness in this module. The records will include a variety of patient and clinical details, including age, gender, and medical history. Next, clean up the data to get rid of any unnecessary characteristics, outliers, or missing values that could compromise the model's accuracy. Train a classification model with SVM or other machine learning algorithms.

User Search Query

Patients and medical professionals can access pertinent medical data from the illness risk prediction system with the help of the User Search Query Module. Using an easy-to-use search interface, users can query the dataset for pertinent patient records or medical insights by entering specified criteria or keywords. Every patient in this system has an ID and password that are exclusive to them and the medical facility. When a patient uses an electronic health record (EHR), the patient's identity can be confirmed by the EHR by requesting their ID and password. Subsequently, the user can look for disease information by symptom. The User Search Query Module improves user productivity and makes evidence-based healthcare decision-making easier by enabling smooth data retrieval.

Query Processing using SVM:

The Support Vector Machine (SVM) algorithm, which is a component of machine learning, is utilized by the Query Processing using SVM Module to process user queries and produce risk projections for renal disease. The module uses the trained SVM model to evaluate pertinent features and calculate the probability of disease occurrence after receiving input data from users. By utilizing SVM's predictive powers, it generates fast and accurate risk evaluations that assist patients and healthcare providers in making therapeutic decisions. Additionally, the module allows for real-time query processing, guaranteeing users receive predictive insights quickly. Through the integration of machine learning into the query processing pipeline, the system's capacity to predict illness risk becomes more accurate and reliable. Using the SVM technique, determine which features are most important for aiding in the diagnosis of an illness. The disease prediction module can utilize a machine learning technique, such as SVM classification, to forecast the disease based on the user's symptoms once the pertinent features have been retrieved.

Prescription Data Sharing:

This module can assist in protecting patient privacy and preventing unwanted access to private medical data. The physician receives information about the anticipated illness. The doctor can see patient information here and recommend medicines. Using a safe random number generator, create a random encryption key. The prescription can be encrypted using AES encryption by utilizing the encryption key. The encrypted data can then be stored in a secure database. Give the search user access to the secret key and encrypted prescription. With the secret key, the user can decrypt and access the prescription.

V. SUPPORT VECTOR MACHINE

SVM Classification

A supervised machine learning approach called Support Vector Machine (SVM) can be applied to regression and classification issues. It is typically utilized in categorization tasks, though. Plot each piece of data in this work as a point

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in n-dimensional space, with each feature's value representing the count of a certain coordinate. Next, we carry out the classification process by identifying the hyper-plane that effectively separates the two classes. To put it simply, support vectors are the coordinates of each individual observation. The most effective method for separating the two classes (hyper-plane/line) is Support Vector Machine. The line with the largest margin to both groups is the hyperplane.

Higher dimensional environments are more effective for Support Vector Machines. Even with data sets where there are more dimensions than samples, it works incredibly well. This is primarily due to the kernel technique, which we will discuss in a later section. Additional benefits of Support Vector Machines over other categorization techniques like k-nearest neighbor or deep neural networks are memory efficiency, speed, and overall accuracy.

Hyperplane

The two-dimensional linearly separable data can be separated by a line. The function of the line is y=ax+by. We rename x with x1 and y with x2 and we get:

$ax1-x2+b=0$

If we define $x = (x1,x2)$ and $w = (a,-1)$ we get:

$w \cdot x+b=0$

Two-dimensional vectors serve as the foundation for this equation. In actuality, though, it also functions for any number of dimensions. This is the hyperplanes equation.

Classifier

Once we have the hyperplane, we can then use the hyperplane to make predictions. We define the hypothesis function h as:

$h(xi)=\{+1 \text{if } w \cdot x+b \geqslant 0$

$h(xi)=\{-1 \text{if } w \cdot x+b<0$

The point above or on the hyperplane will be classified as class +1, and the point below the hyperplane will be classified as class -1.

Essentially, the SVM learning algorithm's objective is to locate a hyperplane that can reliably separate the data. These hyperplanes could be numerous. And we must locate the finest one, also known as the ideal hyperplane.

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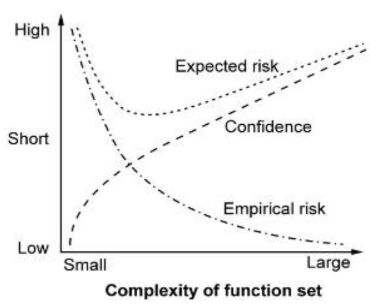

Fig .3 SVM Graph Model

VI. ADVANCED ENCRYPTION STANDARD

Data is encrypted and decrypted using a block cipher by the Advanced Encryption Standard (AES) algorithm, which is a symmetric encryption algorithm. The standard defines three key sizes: AES-128, AES-192, and AES-256. The algorithm consists of the following steps:

Key Expansion: The 128-bit, 192-bit or 256-bit encryption key is expanded into a key schedule of 10, 12, or 14 round keys, respectively. The round keys are derived from the original encryption key using a key schedule algorithm.

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Initial Round: The plain text is divided into 128-bit blocks and XORed with the first round key.
Rounds: The encryption process consists of a set of rounds (10, 12, or 14) that operate on the state of the cipher. Each round consists of four transformations: SubBytes, ShiftRows, MixColumns, and AddRoundKey.
SubBytes: Each byte of the state is replaced with a corresponding byte from a substitution box (S-box). This step provides confusion and helps to prevent linear cryptanalysis.
ShiftRows: Each row of the state is shifted cyclically a certain number of steps. The second row is shifted one step to the left, the third row is shifted two steps to the left, and the fourth row is shifted three steps to the left.
MixColumns: Each column of the state is multiplied with a fixed polynomial. This step provides diffusion and helps to prevent differential cryptanalysis.
AddRoundKey: The round key for the current round is XORed with the state.
Final Round: The final round is the same as the previous rounds except that it does not include the MixColumns transformation.
Output: The resulting cipher text is the final state of the cipher.
The encryption procedure is reversed during decryption. The final round key is XORed with 128-bit blocks of the ciphertext. The rounds are then carried out using the inverse of each transformation, in reverse order. The original plain text is what remains in the end.

VII. RESULT AND EXECUTION

The results and discussion section of the project on kidney disease prediction would typically detail the outcomes of implementing the proposed strategy, including the performance of the machine learning models, the effectiveness of the predictive algorithms, and the impact on healthcare delivery and patient outcomes. The proposed approach has been implemented using Python as front end and MySQL as back end software.

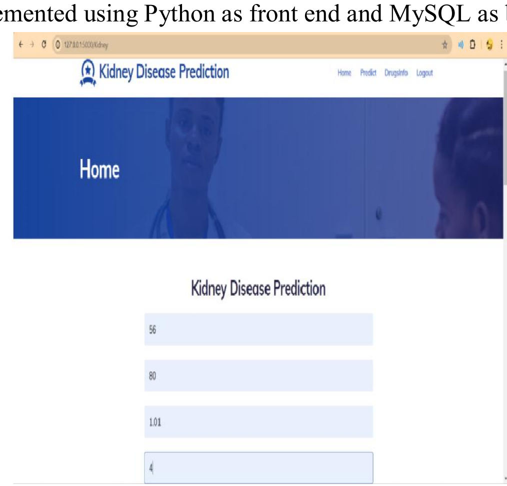

Fig .4 Input Patient Data

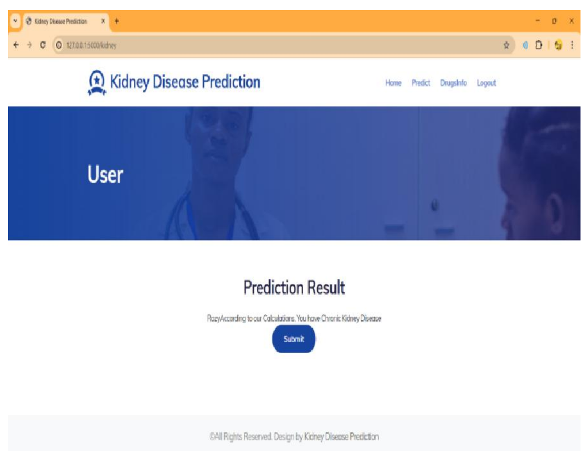

Fig .5 Disease Prediction Result

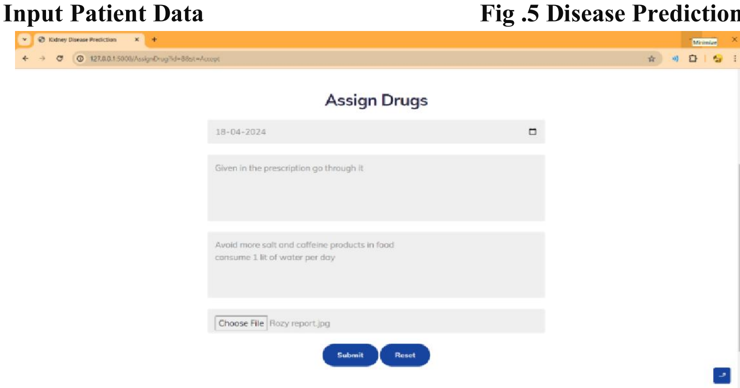

Fig .6 Data Decrypt and Access

VIII. CONCLUSION

To sum up, the illness risk prediction system is a noteworthy development in medical technology that provides a variety of options for early identification, individualized treatment, and resource optimization in the management of renal disease. A promising method in healthcare that can enhance patient privacy while maintaining accurate disease prediction is disease prediction utilizing symptom data with a classifying disease dataset using SVM algorithm and encrypting the disease information using AES algorithm. The AES algorithm's encryption of the disease dataset guarantees patient privacy by limiting access to the decryption key to authorized individuals only. The system can promote advancements in renal disease management, improve clinical decision-making, and improve patient outcomes through its applications in population health management, research, and customized healthcare. As time goes on, more research and application of these cutting-edge techniques could transform healthcare delivery and advance global public health programs.

REFERENCES

[1] Kwan-Loo, Kevin B., José C. Ortíz-Bayliss, Santiago E. Conant-Pablos, Hugo Terashima-Marín, and P. Rad. "Detection of violent behavior using neural networks and pose estimation." IEEE Access 10 (2022): 86339-86352.
[2] Adil, Muhammad, Saqib Mamoon, Ali Zakir, Muhammad Arslan Manzoor, and Zhichao Lian. "Multi scale-adaptive super-resolution person re-identification using GAN." Ieee Access 8 (2020): 177351-177362.
[3] Alansari, Mohamad, Oussama Abdul Hay, Sajid Javed, Abdulhaid Shoufan, Yahya Zweiri, and Naoufel Werghi. "GhostFaceNets: Lightweight Face Recognition Model From Cheap Operations." IEEE Access (2023).
[4] Deng, Jiankang, Jia Guo, Evangelos Ververas, Irene Kotsia, and Stefanos Zafeiriou. "Retinaface: Single-shot multi-level face localisation in the wild." In Proceedings of the IEEE/CVF conference on computer vision and pattern recognition, pp. 5203-5212. 2020.
[5] Deng, Jiankang, Jia Guo, Niannan Xue, and Stefanos Zafeiriou. "Arcface: Additive angular margin loss for deep face recognition." In Proceedings of the IEEE/CVF conference on computer vision and pattern recognition, pp. 4690-4699. 2019.
[6] Zhu, Yanjia, Hongxiang Cai, Shuhan Zhang, Chenhao Wang, and Yichao Xiong. "Tinaface: Strong but simple baseline for face detection." arXiv preprint arXiv:2011.13183 (2020).
[7] Feng, Yao, Fan Wu, Xiaohu Shao, Yanfeng Wang,and Xi Zhou. "Joint 3d face reconstruction and dense alignment with position map regression network."
[8] Ferrari, Claudio, Stefano Berretti, and Alberrto Del Bimbo. "Extended youtube faces: a dataset for heterogeneous open-set face identification." In 2018 24th International Conference on Pattern Recognition (ICPR), pp. 3408-3413. IEEE, 2018.
[9] Lin, Yiming, Shiyang Cheng, Jie Shen, and Maja Pantic. "Mobiface: A novel dataset for mobile face tracking in the wild." In 2019 14th IEEE International Conference on Automatic Face & Gesture Recognition (FG 2019), pp. 1-8. IEEE, 2019.
[10] Wang, Hao, Yitong Wang, Zheng Zhou, Xing Ji, Dihong Gong, Jingchao Zhou, Zhifeng Li, and Wei Liu. "Cosface: Large margin cosine loss for deep face recognition." In Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 5265-5274. 2018.