

Latency-Aware Encrypted Data Processing Framework for Distributed Medical Diagnostics at the Network Edge

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Abstract

The rapid growth of digital healthcare systems has increased the demand for intelligent and secure diagnostic solutions capable of handling sensitive medical data. Traditionally, disease prediction relied on manual analysis and rule-based approaches, which were limited in processing large-scale and complex datasets. With the evolution of machine learning, automated diagnostic systems have emerged; however, many existing methods lack proper data security and struggle with imbalanced datasets, resulting in reduced accuracy and reliability. These challenges highlight the need for a robust and secure analytical framework. The primary objective of this study is to develop a secure and accurate disease prediction system for healthcare datasets such as heart disease and hypothyroid conditions. Traditional systems often fail due to inadequate preprocessing, poor feature handling, and absence of secure data processing mechanisms. Additionally, class imbalance further impacts model performance and prediction consistency. To address these issues, a comprehensive framework is proposed that integrates data preprocessing, exploratory data analysis, and synthetic data balancing using Synthetic Minority Over-sampling Technique (SMOTE). Multiple machine learning models, including Naive Bayes (NB), Passive Aggressive (PA), Ridge Classifier (RC), and Extreme Gradient Boosting (XGB), are utilized for prediction. A privacy-preserving encryption mechanism is incorporated to ensure secure data handling, and a Flask-based interface enables efficient user interaction and real-time prediction. The proposed system achieves high performance, with XGB attaining 100.00% accuracy on the heart dataset and 99.89% on the hypothyroid dataset. The framework ensures accuracy, security, and scalability for reliable healthcare decision support.

Keywords: Disease Prediction, Machine Learning, SMOTE, Data Security, Extreme Gradient Boosting (XGBoost), Healthcare Analytics

1. Introduction

The healthcare sector remains a critical pillar for national development, as the rise of contagious and chronic diseases continues to impact global populations and economies [1]. In recent years, the adoption of Internet of Things (IoT) based remote healthcare systems, often referred to as smart healthcare, has significantly improved patient monitoring by enabling continuous observation without requiring physical hospital visits [2]. Despite these advancements, the widespread use of wearable and connected medical devices has introduced serious concerns regarding data confidentiality and integrity, posing risks to patient privacy and overall system security [3]. Moreover, conventional cloud-based analytical frameworks, although computationally powerful, suffer from high latency, making them less suitable for time-sensitive medical decision-making scenarios [4]. To address these challenges, recent research emphasizes the need for decentralized and secure analytical frameworks. In this context, edge computing has emerged as a promising solution by bringing computational capabilities closer to the data source, thereby reducing response time, and improving real-time decision support [5]. At the same time, advanced cryptographic techniques such as homomorphic encryption enable secure processing of sensitive healthcare data without exposing it in plaintext form, as shown in figure 1. This ensures that

patient information remains protected even during analytical operations, enhancing trust and compliance with privacy standards.

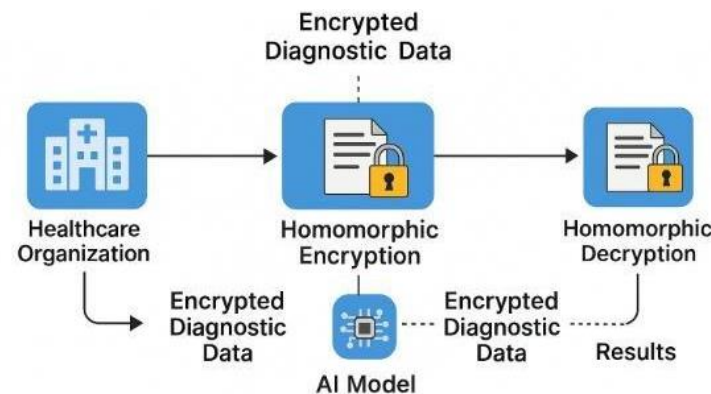


Figure. 1: Homomorphic encryption workflow in a healthcare AI

Motivated by these requirements, this study focuses on developing a secure and efficient healthcare prediction framework that integrates machine learning with privacy-preserving mechanisms. The objective is to enable accurate and low-latency disease prediction while maintaining data confidentiality. This approach addresses the critical challenge of balancing real-time analytics with secure data handling in modern healthcare environments [6].

2. LITERATURE SURVEY

Anghel, et al. [7] Developed a domain such as Ambient Assisted Living (AAL) or healthcare can greatly benefit from the IoT and edge computing advancements. AAL focuses on bringing aid and personalized assistance to daily activities and offering proactive interventions to enhance the quality of life for individuals. The applications in the current state of the art vary from basic sensing applications such as fall detection, medication monitoring, and remote follow-up, to more complex tasks such as personalized care and cognitive decline management. Mandarino, et al. [8] Proposed Edge HR, a blockchain-based electronic health record (EHR) system that addresses the current limitations of using public blockchain for health data storage and management. To solve the issues related to cost and lack of performance in current healthcare blockchain solutions, the authors propose a hybrid storage solution, where medical records are stored locally, on users' devices, while the blockchain is used to trace these records, ensuring security and accessibility. By decentralizing storage and control, this solution enhances privacy and reduces the risk of unauthorized access and improves the constraints of storage by improving the use of smart contracts and design patterns to efficiently manage patients' data.

Ejaz, et al. [9] introduced a framework that used edge computing to reduce latency and increase data privacy while reducing the amount of sensitive data transferred to the cloud. The blockchain component ensures data security and provides a decentralized method to handle health data securely. Adeniyi, et al. [10] proposed a blockchain-based smart healthcare system that focuses on data protection, which can significantly enhance privacy and security in medical data handling. Attribute-Based Signcryption (ABSC) is a relatively new encryption technique that combines attribute-based encryption with attribute-based signing mechanisms.

Sun, et al. [11] developed a fine-grained attribute access control model for EHRs, enabling scalable and privacy-aware healthcare data exchange. However, while ABSC provides high security, its computational resource consumption is relatively high, which may make it unsuitable for low-power devices in medical environments. Nevertheless, the efficient allocation and management of multiple encryption keys remained a challenge for this approach. He, et al. [12] Developed that ABSC could

ensure data privacy and security in cross-platform healthcare data sharing. By introducing a revocation mechanism, user access permissions can be dynamically updated when user privileges change, further enhancing the security of data sharing. Despite the excellent security provided by ABSC, its computational complexity remains a bottleneck, especially when it comes to large-scale medical data sharing.

Patil et al. [13] implemented a chain-of-custody model with ABSC, ensuring secure traceability of medical data in multi-role scenarios, a novel framework that combines blockchain, edge computing, and ABSC in a unique way to address the specific needs of IoMT environments. While blockchain has been widely recognized for its ability to ensure data immutability and transparency, and ABSC has been proven to provide fine-grained access control, their integration into an efficient, decentralized system for the IoMT has not been fully explored. Raj et al. [14] presented a novel framework for optimizing cooperative networks at the network's periphery. In addition, the collaboration of edge nodes can be optimized to boost performance on specific activities. In order to demonstrate the efficacy of the proposed architecture, real datasets collected from the elderly and their wearable sensors are employed. Extensive experimentation is also helpful in verifying the effectiveness of the given optimization algorithm.

Xu et al. [15] introduced an extensive survey of deep reinforcement learning (DRL) in the context of medical imaging and radiation therapy. It covers DRL's basic concepts and algorithms and discusses its applications in lesion localization, classification, registration, segmentation, and treatment planning. Moshawrab et al. [16] presented the state-of-the-art smart wearables that can detect and monitor cardiovascular diseases (CVDs), the leading cause of death worldwide. They focus on the types, features, and applications of smart wearables, such as smartwatches, smart bands, smart rings, and smart glasses, that can measure various physiological signals, such as electrocardiogram (ECG), photoplethysmogram (PPG), blood pressure (BP), and heart rate (HR) signals. Robinson et al. [17] developed a system integrating smart IoT devices to allow access to patient data via the internet using cloud computing. By facilitating the acquisition and accumulation of data needed to monitor patient health, physicians were better able to solve their health problems in timely fashion.

3. Proposed System

The proposed methodology establishes a structured analytical framework for analysing medical datasets using data-driven techniques and secure processing mechanisms. The analytical pipeline begins with dataset acquisition and organization, followed by preprocessing steps to clean and structure the data. This includes handling missing values, encoding categorical attributes, and ensuring consistency across features. The processed data is then prepared for analysis by converting it into numerical formats suitable for computation.

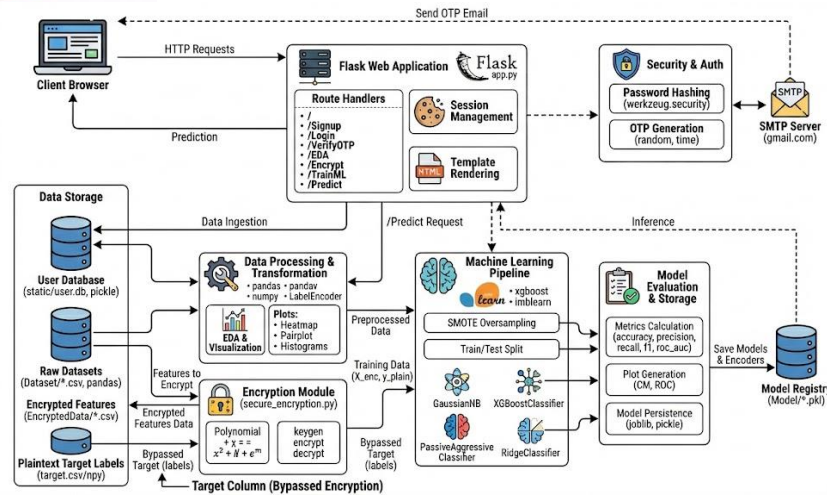


Figure. 2: Proposed system architecture.

Multiple classification techniques are applied to evaluate patterns and relationships within the data, enabling accurate prediction of medical conditions. In addition, a privacy-preserving mechanism is incorporated to protect sensitive information during processing. A web-based interface allows users to interact with the system for dataset upload, visualization, training, and prediction tasks, as shown in figure 2. A lightweight storage mechanism is used to manage trained models and user authentication data, while a server component enables remote access and prediction. Continuous evaluation and retraining help improve performance and adapt the system to newly available data.

1. Web Environment & UI Initialization

The execution begins with the setup of the browser-supported graphical interface and the frontend interaction layer.

- **Web-Based Interface:** Provides a centralized dashboard for user operations, including secure login, dataset selection, and real-time analysis.
- **Request Handling:** Captures user inputs and local file uploads (CSV/Tabular), preparing them for transmission to the backend modules.
- **Accessibility Layer:** Ensures that complex medical data operations are manageable through intuitive navigation and visual feedback.

2. Flask Application Server

The Flask framework serves as the central orchestrator, managing the logic and communication between the client and the analytical engine.

- **Central Controller:** Receives HTTP requests from the UI and routes them to the appropriate processing or training modules.
- **Communication Management:** Coordinates the flow of data between the encryption module, the database, and the machine learning models.
- **Remote Access Enablement:** Facilitates a distributed environment where users can perform analysis from varying locations via a secure server link.

3. User Database & Authentication Management

A secure storage perimeter is established to protect the system from unauthorized access.

- **Authentication Storage:** A lightweight database maintains user profiles, including usernames and encrypted password hashes.
- **Verification Logic:** Invoked during registration and login to ensure that only authorized personnel can access sensitive medical functionalities.
- **Session Security:** Manages user-related information securely to maintain data privacy throughout the analytical session.

4. Medical Data Ingestion

The system processes specialized medical datasets to drive the diagnostic models.

- **Dataset Sources:** Primary inputs include heart disease and hypothyroid datasets containing patient vitals and measurements.
- **Tabular Organization:** Data is structured into feature columns (diagnostic indicators) and target labels (diagnosis status) for supervised learning.
- **Dual-Purpose Utility:** These datasets provide the foundation for both initial model training and rigorous cross-validation.

5. Data Preprocessing & Transformation

Raw medical records are refined into a clean, consistent format suitable for machine learning algorithms.

- **Missing Value Handling:** Inbuilt techniques are used to remove or impute null entries, ensuring dataset integrity.
- **Attribute Selection:** Irrelevant features are stripped away to reduce noise and improve model focus on critical diagnostic indicators.
- **Categorical Encoding:** Converts qualitative data into numerical representations, allowing the mathematical models to process non-numeric patient details.

6. Privacy-Preserving Data Encryption

A critical security layer is applied to protect sensitive patient information during the processing phase.

- **Secure Numerical Representation:** The encryption module transforms original data points into secure formats that mask identity while preserving utility.
- **Confidentiality Maintenance:** Ensures that sensitive attributes remain protected during storage and transit between the client and server.
- **Risk Mitigation:** Minimizes the threat of unauthorized data exposure or leaks during high-performance computation.

7. Classification Model Implementation

The framework employs a diverse ensemble of classifiers to ensure robust and accurate diagnostic predictions.

- **NB:** Applies probabilistic analysis to determine the likelihood of a medical condition based on input features.
- **PA:** An online learning algorithm that updates model parameters dynamically based on misclassification patterns.

- **XGB:** Utilizes gradient boosting techniques to provide high-accuracy results for complex medical patterns.
- **RC:** Applies linear classification with built-in regularization to prevent overfitting on smaller medical datasets.

8. Performance Evaluation & Metrics

The system utilizes a comprehensive suite of diagnostic metrics to verify the reliability of the models.

- **Core Metrics:** Evaluates performance using Accuracy, Precision, Recall, and F1-score.
- **Detailed Analysis:** Incorporates Specificity and AUC (Area Under the Curve) to assess the model's ability to distinguish between classes.
- **Visual Diagnostics:** Generates confusion matrices and ROC curves to provide users with a transparent view of model strengths and weaknesses.

9. Prediction & Output Generation

The inference engine generates real-time results based on new patient inputs or uploaded test files.

- **Model Inference:** Processes pre-processed and encrypted inputs through the trained classification pipeline.
- **Structured Output:** Displays predicted diagnostic labels and additional interpretative details directly on the user interface.
- **Decision Support:** Enables medical professionals to make informed, data-driven decisions backed by multi-model analysis.

10. Remote Prediction Workflow

The architecture is designed for scalability and flexibility across distributed medical environments.

- **Client-Server Communication:** Supports a workflow where users can upload data from various systems and receive predictions from a centralized server.
- **Remote Interaction:** Ensures that the diagnostic framework is accessible regardless of the user's local hardware constraints.

11. Model Evaluation & Adaptive Updating

The framework is designed to evolve alongside changing medical data patterns and new research.

- **Continuous Evaluation:** Regularly assesses model accuracy as new data flows through the system.
- **Retraining Mechanism:** Supports an adaptive update cycle where models are retrained with fresh data to improve precision.
- **Reliability Enhancement:** Ensures the system remains effective and up-to-date, maintaining long-term reliability for evolving medical datasets.

4. Results description

The results of the analytical framework demonstrate the effectiveness of integrating preprocessing, encryption, and multiple machine learning models for disease prediction. The system evaluates the performance of NB, PA, XGB, and RC using healthcare datasets under a consistent experimental setup.

Performance is assessed using standard evaluation metrics such as accuracy, precision, recall, F1-score, specificity, and ROC-AUC. Visualization techniques including confusion matrices and ROC curves are used to provide deeper insights into model behaviour. The application of SMOTE improves class balance, contributing to enhanced predictive performance. Comparative analysis of models highlights the strengths of ensemble and linear approaches in handling medical data. The results validate the reliability and robustness of the framework in generating accurate predictions.

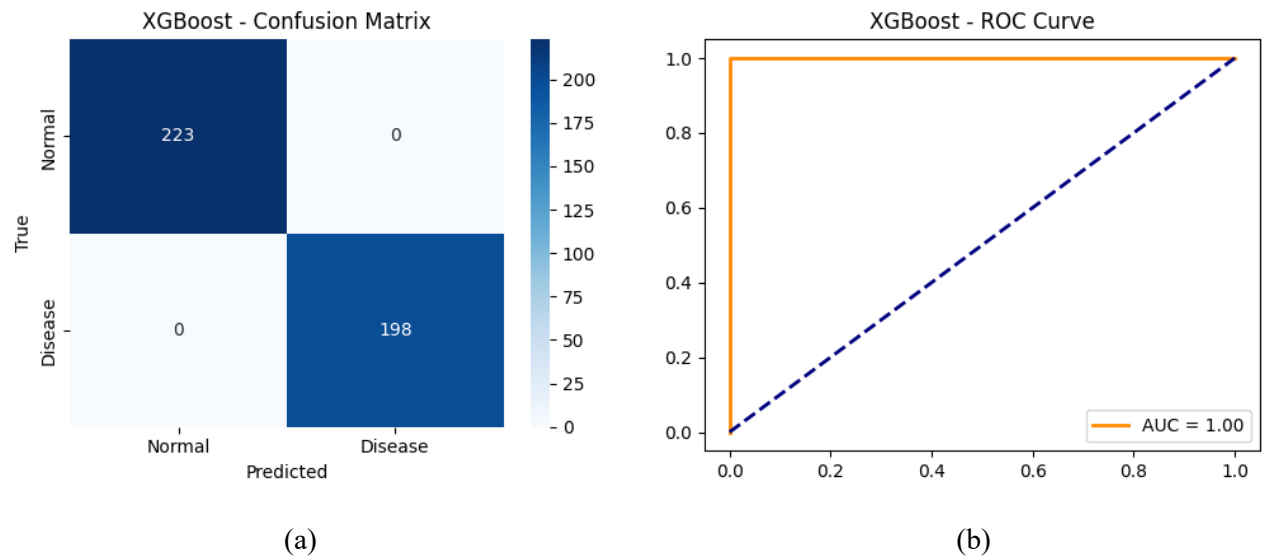
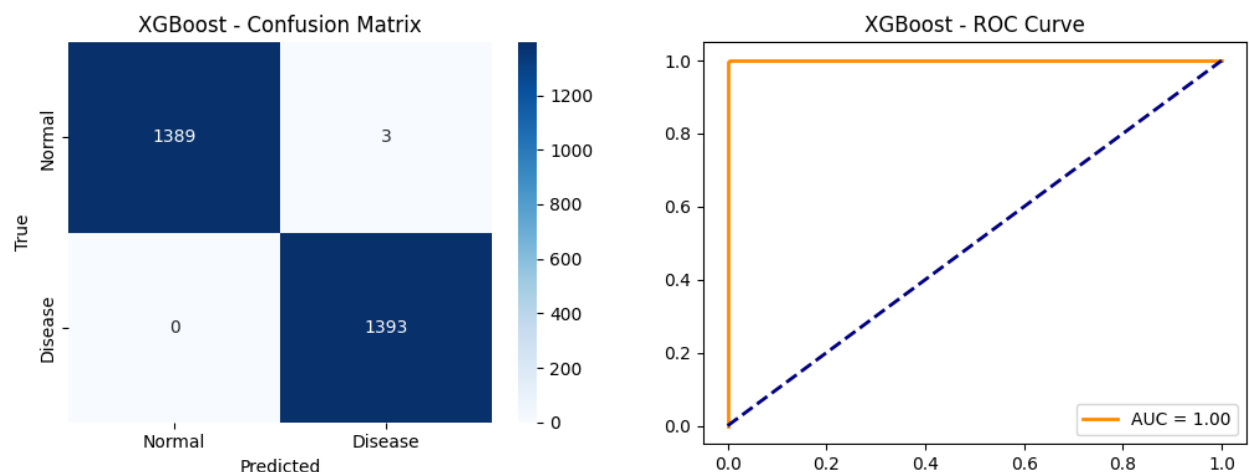


Figure. 3 (a, b): Confusion Matrix and ROC obtained for XGB (Heart Dataset)

Figure 3 (a) illustrates the confusion matrix of the XGB model, showing the classification results for normal and disease categories with complete accuracy. The matrix indicates that all instances are correctly classified, with no misclassification observed between the classes. This reflects perfect prediction performance in terms of true positives and true negatives. The visualization demonstrates the model's ability to clearly distinguish between the two categories without error. It highlights the effectiveness of the model in handling complex healthcare data.

Figure 3 (b) illustrates the ROC curve of the XGB model, representing the relationship between true positive rate and false positive rate across different threshold values. The curve reaches the top-left corner, indicating optimal classification performance. The area under the curve (AUC) is equal to 1.00, which signifies perfect discrimination between classes. This confirms the robustness and high efficiency of the model. The visualization supports comparison with other models and validates its effectiveness.



(a)

(b)

Figure. 4 (a, b): Confusion Matrix and ROC obtained for XGB (Hypothyroid Dataset)

Figure 4 (a) illustrates the confusion matrix of the XGB model applied to the hypothyroid dataset, presenting the classification outcomes for normal and disease categories. The matrix shows an almost perfect classification performance with only a negligible number of misclassifications. It highlights that the model accurately identifies both normal and disease instances with very high precision. The distribution of true positives and true negatives dominates the matrix, indicating strong predictive capability. This visualization demonstrates the effectiveness of the model in handling complex healthcare data.

Figure 4 (b) illustrates the ROC curve of the XGB model for the hypothyroid dataset, showing the relationship between true positive rate and false positive rate across different threshold values. The curve reaches the optimal region near the top-left corner, indicating excellent classification performance. The area under the curve is equal to 1.00, representing perfect discriminative ability. This confirms the robustness and reliability of the model in distinguishing between classes. The visualization supports comparison with other models and highlights its superiority.

Table. 1: Comparative analysis for heart dataset

Algorithm	Accuracy	Precision	Recall	F1-Score	Specificity	AUC
NB	83.14%	83.18%	83.29%	83.13%	80.72%	0.90
XGB	100.00%	100.00%	100.00%	100.00%	100.00%	1.00
PA	75.77%	77.74%	74.89%	74.84%	89.69%	0.84
RC	82.90%	83.22%	83.21%	82.90%	78.03%	0.90

The above table 1 presents the comparative performance analysis of four machine learning models, namely NB, XGB, PA, and RC, evaluated on the heart dataset. The evaluation is carried out using key metrics such as accuracy, precision, recall, F1-score, specificity, and AUC to ensure a comprehensive assessment of classification performance. Among all models, XGB demonstrates the highest accuracy of 100.00%, indicating perfect classification capability on the given dataset. NB and RC also show competitive performance with accuracy scores of 83.14% and 82.90% respectively, reflecting stable and reliable predictions. PA exhibits comparatively lower accuracy at 75.77%, though it maintains a relatively high specificity of 89.69%. The AUC values further confirm that XGB achieves the best discriminative performance with a score of 1.00, while NB and RC follow with 0.90.

Table. 2: Comparative analysis for hypothyroid dataset

Algorithm	Accuracy	Precision	Recall	F1-Score	Specificity	AUC
NB	67.94%	74.61%	67.94%	65.61%	93.97%	0.87
XGB	99.89%	99.89%	99.89%	99.89%	99.78%	1.00
PA	50.74%	75.19%	50.72%	34.92%	1.44%	0.74
RC	86.07%	86.28%	86.07%	86.05%	89.87%	0.94

The above table 2 presents the comparative performance of NB, XGB, PA, and RC models evaluated on the hypothyroid dataset using multiple classification metrics. The results indicate that XGB achieves the highest accuracy of 99.89%, demonstrating superior predictive capability and consistency across all evaluation measures. RC also performs well with an accuracy of 86.07%, showing balanced performance in terms of precision, recall, and F1-score. NB provides moderate performance with an accuracy of 67.94%, though it maintains a high specificity of 93.97%, indicating strong negative class identification. In contrast, PA shows the lowest accuracy of 50.74% and a significantly low specificity of 1.44%, reflecting poor generalization on this dataset. The AUC values further confirm that XGB is the most reliable model with a score of 1.00, followed by RC at 0.94.

Prediction Results

ESTBPS	CHOL	FBS	RESTECG	THALACH	EXANG	OLDPEAK	SLOPE	CA	THAL	PREDICTION
	212	0	1	168	0	1.0	2	2	3	No Heart Disease
	203	1	0	155	1	3.1	0	0	3	No Heart Disease
	174	0	1	125	1	2.6	0	0	3	No Heart Disease
	203	0	1	161	0	0.0	2	1	3	Heart Disease
	294	1	1	106	0	1.9	1	3	2	No Heart Disease
	248	0	0	122	0	1.0	1	0	2	Heart Disease
	318	0	2	140	0	4.4	0	3	1	No Heart Disease
	289	0	0	145	1	0.8	1	1	3	No Heart Disease
	249	0	0	144	0	0.8	2	0	3	Heart Disease

Figure. 5: Prediction results for heart dataset

Figure 5 illustrates the prediction results generated by the system for the heart dataset, displaying the classification outcomes based on input feature values. The table presents multiple clinical attributes along with the corresponding predicted class indicating the presence or absence of heart disease. The results demonstrate how the trained model processes input data and produce interpretable outputs for decision support. It highlights the system's ability to classify instances accurately using learned patterns from the dataset. The structured format enables clear visualization of predictions for multiple records simultaneously.

Prediction Results

TT4 MEASURED	TT4	T4U MEASURED	T4U	FTI MEASURED	FTI	TBG MEASURED	TBG	REFERRAL SOURCE	PREDICTION
	125	1	72	1	10	0	0	1	Abnormal
	102	0	146	0	234	0	0	4	Abnormal
	109	1	48	1	22	0	0	4	Abnormal
	175	0	146	0	234	0	0	4	Abnormal
	61	1	44	1	199	0	0	3	Abnormal
	183	1	88	1	45	0	0	4	Abnormal
	72	1	49	1	207	0	0	4	Abnormal
	80	1	27	1	17	0	0	3	Normal
	123	1	50	1	35	0	0	3	Abnormal
	83	1	46	1	227	0	0	3	Abnormal
	115	1	53	1	23	0	0	3	Abnormal
	152	1	57	1	58	0	0	4	Abnormal
	171	1	71	1	56	0	0	4	Abnormal

Figure. 6: Prediction results for hypothyroid dataset

Figure 6 illustrates the prediction results generated by the system for the hypothyroid dataset, presenting classification outcomes based on clinical and laboratory test attributes. The table displays multiple input features along with the corresponding predicted class indicating normal or abnormal thyroid condition. The results demonstrate how the trained model analyses complex medical parameters and produce meaningful predictions for each record. It highlights the system's capability to process real-time input data and deliver accurate diagnostic outputs. The structured representation allows clear interpretation of prediction results across multiple instances.

5. Conclusion

The study presents a secure and intelligent diagnostic framework that integrates data preprocessing, encryption, and machine learning techniques for effective disease prediction. The implementation combines multiple classifiers including NB, PA, RC, and XGB to evaluate predictive performance on heart and hypothyroid datasets. Among these models, XGB consistently achieves the highest accuracy, reaching 100.00% for heart data and 99.89% for hypothyroid data, indicating superior learning capability and robustness. The use of SMOTE significantly improves class balance, leading to better recall and overall model stability. Encryption techniques ensure data privacy during processing, enhancing the reliability of the analytical pipeline. Comparative analysis shows clear performance improvements over traditional approaches, particularly in terms of accuracy, AUC, and classification consistency. Visualization through ROC curves and confusion matrices further validates model effectiveness. The integration of a Flask-based interface enables seamless user interaction, real-time prediction, and efficient system usability. The framework demonstrates high accuracy, security, and scalability, making it suitable for real-world healthcare applications.

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