

Original Article

An Interpretable and Privacy-Aware Machine Intelligence Framework for Accurate Disease Prediction using Electronic Health Data

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Abstract - The development of EHDs has completely changed healthcare operations through simplification of the process of using patient data to diagnose and provide appropriate treatment. Some success has already been seen within this field of research, although it is challenging to implement MI models in practical applications. The limitations of current work illustrate the necessity of having a unified MI approach which would guarantee the clinical appropriateness, transparency, privacy, and usability of this system. The goal of the research paper under consideration is to propose a three-stage process to design an MI framework for disease prediction that will be understandable and preserve personal data. The first step is to obtain EHD from many different places, some of which are organized and others of which are not. After that, the data are preprocessed, features are extracted, and finally, the data are anonymized. The next step is to train and evaluate different Machine Learning (ML) models, like Convolutional Neural Networks (CNN), Long Short-Term Memories (LSTM), and others. An additional Explainable AI (XAI) layer is introduced into the analysis to help comprehend the findings. The next step of the research, which will happen in Phase 3 of the study, is cross-demographic validation and pilot test of the IPAMI Framework in the clinical environment. This research will bring improvements to the decision-making processes within the healthcare sector and result in the better well-being of patients due to potential application of MI systems in practice.

Keywords - Clinical decision support, Disease prediction, Electronic health data, Explainable AI, Machine intelligence.

1. Introduction

Preservation of privacy is increasingly becoming an important requirement in the contemporary healthcare system since the medical data may include sensitive information about the patients, which should be protected during the processing and analysis of such information [1]. Artificial intelligence and machine learning in healthcare are currently offering many possibilities for disease prediction, diagnostics, and personalized medical services, at the same time raising a number of privacy and security issues [2]. Privacy preservation in mental health care applications is especially important as the psychological and behavioral data might contain highly sensitive information [3].

The growing availability of electronic medical records is additionally creating the necessity for secure and efficient retrieval and processing of patient information while not exposing any confidential information [4]. The federated learning approach allows multiple healthcare institutions to work together in developing machine learning models using the available information from different parties, but without

actually exchanging the actual datasets [5]. Privacy-aware learning approaches could also be combined with advanced learning algorithms to perform early detection of diseases while protecting any sensitive information [6]. Combining privacy protection with Big Data analysis has significantly increased the chances of carrying out collaborative healthcare analysis in distributed environments [7].

Therefore, federated learning has recently been highly regarded as a means of privacy-preserving analysis in smart healthcare applications, especially since medical data can be stored within the original organization while model knowledge is being exchanged collaboratively [8]. Distributed prediction using edge-based healthcare infrastructures can also be possible through analyzing medical data near the location of their generation [9]. Privacy-preserving disease prediction has been studied for various diseases in healthcare applications, which have proven the feasibility of gaining relevant results while guaranteeing patient privacy [10]. Machine learning approaches have been used for privacy-preserving cancer diagnosis applications,



where the protection of confidential medical data has been taken into consideration along with clinical prediction [11].

Privacy-preserving healthcare intelligence analysis with the use of Internet of Things technologies is also possible for the continuous acquisition of data and the diagnosis of multiple diseases [12].

Techniques that are based on encryption algorithms constitute yet another method to protect health care data in a computational environment. With fully homomorphic encryption, it is possible to conduct predictive calculations using the encrypted data, and thereby offer another dimension of privacy in the health care sector [13].

Likewise, anonymization methods like k-anonymity minimize the chances of patient identification in a health care dataset, making it valuable for processing [14]. Deep learning has also found its place in privacy-aware health care recommendation systems for large-scale health care data processing [15].

The aim of this project is to address these challenges by developing an AI-based framework that is consistent across all healthcare settings, ensures patient privacy, and is highly accurate and interpretable.

A wide range of different MI models that have been trained using structured as well as unstructured EHD would be investigated in this research. Some of the MI models include Convolutional Neural Network (CNN), LSTM network, and ensemble learning. Objectives of the project are to evaluate different MI techniques for disease prediction using heterogeneous health data sets. Also, development of interpretable machine learning models through XAI tools like SHAP and LIME. This study proposes a modular, scalable, and secure framework for MI that is able to effectively predict diseases in different populations.

Some of the most important aspects of the study are:

- Inclusion of explainable AI modules to boost physician confidence and transparency of the algorithm.
- Introduction of privacy-preserving workflows which make use of cryptographic methods such as homomorphic and Blowfish.
- Adoption of conventional preprocessing steps to ensure the compatibility of data.
- Conduction of a clinical pilot to evaluate usability and performance.

2. Related Works

Kong et al. (2022) developed a framework for the prediction of multitype health care data in the edge environment under privacy preservation. The study explains

the problems that edge computing is facing owing to the heterogeneity of health data and emphasizes the importance of privacy preservation in prediction frameworks [16].

Khalid et al. (2023) described privacy-preserving artificial intelligence techniques used for healthcare applications. In the study, various privacy-preservation techniques utilized in the healthcare sector were discussed. These techniques included federated learning, differential privacy, encryption, and anonymization. Strengths and weaknesses of each technique were explained [17].

Lu and Uddin (2023) conducted a review on machine learning using graphs for disease prediction from EHR. In the study, recent developments in the field of graph machine learning, along with its ability to learn complex relations among patients, diseases, and healthcare data was described [18].

Liu et al. (2025) performed systematic reviews and meta-analyses on cardiovascular disease risk prediction models through machine learning based on electronic health records. The research analyzed current prediction strategies and indicated the capability of EHR-based machine learning in enhancing the prediction of cardiovascular risks [19].

Rasmy et al. (2021) introduced a new contextualized embedding pre-trained model named Med-BERT, which is specifically developed for large-scale structured electronic health records. In this way, the research made use of contextualized embeddings of EHR to enhance the predictions of diseases and proved the efficacy of pretrained deep learning models for healthcare application [20].

Li et al. (2020) presented a machine learning-based technique for diagnosing heart disease within e-healthcare systems. This study investigated various classification methods for heart disease prediction and indicated the suitability of machine learning models for making automated clinical decisions [21].

Ghaffar Nia et al. (2023) assessed various artificial intelligence techniques that are employed for the purpose of disease diagnosis and prediction. They compared various techniques and analyzed the impact of different parameters on the diagnosis [22].

Ali et al. (2021) evaluated various supervised machine learning algorithms for predicting heart diseases in terms of their performance. It was shown that different types of classification algorithms can be used for disease prediction, whereas model selection is still necessary for obtaining accurate results [23].

Ibrahim et al. (2021) addressed the problem of health data poverty and the effect it has on providing equal digital

healthcare. This paper emphasized the importance of adequate representation and presence of data for developing and applying AI-based healthcare technologies [24].

Schulz et al. (2021) studied the time aspect of computed and structured diagnoses in EHR data. Their research demonstrates that it is necessary to understand the temporal aspects of EHRs since the temporal structure of diagnosis recording may influence the healthcare data analysis and prediction [25].

Sarwar et al. (2022) considered the secondary use of EHRs in data mining and their main features, as well as challenges associated with it. The problems of data quality, heterogeneity, missing data, and interoperability were identified [26].

Waheed et al. (2022) assessed the role of emerging imaging technologies in the practice of modern radiology. This paper demonstrates the relevance of medical imaging as a key source of information in clinical settings and also identifies the challenges of proper management and interpretation of increasingly complex imaging data [27].

Islam et al. (2023) assessed various imaging modalities and their application in healthcare. The paper provides a review of the existing imaging technologies utilized in clinical diagnosis and stresses the significance of medical imaging data in intelligent healthcare analysis systems [28].

Haveman et al. (2022) explored continuous monitoring of physiological parameters with the help of wearable sensors during daily life activities. The study validated the effectiveness of wearable-based monitoring and the potential of sensor technologies to acquire continuous physiological data from outside the clinical environment [29].

Selvaraju et al. (2022) performed a systematic review of camera-based methods for continuous monitoring of physiological parameters. The paper assesses the potential of camera technologies in non-contact physiological monitoring and their application in continuous healthcare monitoring [30].

Wan and Huang (2025) studied missing value handling methods in machine-learning-based detection systems for behavioral misbehaviors. Despite the focus on intelligent transport systems, the study on missing values' handling is applicable to healthcare since missing values can impair the accuracy of machine learning prediction [31].

Zignoli et al. (2024) analyzed the use of machine learning and continuous glucose monitoring for nutrition customization. The paper demonstrates an example of using physiological data obtained by the continuous monitoring method with machine learning techniques for finding unique

behavioral patterns of patients [32]. Linkon et al. (2024) assessed the feature transformation methods and machine learning models for early diagnosis of diabetes mellitus. The study illustrates how feature representation and machine learning algorithms could be used for detecting diseases using machine learning methods effectively [33].

Nie (2024) analyzed approaches to identifying and handling personally identifiable information to enhance data interoperability. The study underscores the need for correct identification of sensitive data and their appropriate management in cases of health care data integration and exchange [34].

Sreelakshmi and Anoop (2025) present a deep convolutional neural network model that can classify medical data that is collected through computed tomography. This paper shows that deep learning techniques are effective in automated image classification tasks within the context of medical images [35].

3. Research Gap

Privacy-preserving methods like EHGA-DLNN, HELR through CKKS, and k-anonymity mainly concern health care data security, while others concentrate on disease-specific prediction or interpretability of models.

However, a unified approach for heterogeneous EHD processing, privacy preservation, disease prediction, and interpretability remains limited.

The Interpretable and Privacy-Aware Machine Intelligence (IPAMI) Framework addresses this gap through CNN for medical imaging, LSTM for wearable time-series data, RF and SVM for structured EHR data, anonymization for privacy protection, and SHAP and LIME for model interpretability.

3.1. Interpretable and Privacy-Aware Machine Intelligence (IPAMI)

As depicted in Figure 1, the Interpretable and Privacy-Aware Machine Intelligence is based on modular MI systems, which take into account transparency, privacy, and usability aspects. In the first step, structured EHRs, radiological images, and wearable data are obtained. Data preprocessing includes the steps of data cleaning and normalization. The anonymization process (k-anonymity, differential privacy) is employed in order to protect patient privacy.

Neural Networks for image analysis, LSTM neural networks for time-series analysis (vitals), Random Forests and SVMs are implemented. They are trained through stratified cross-validation, and hyperparameters are selected by applying Bayesian optimization. Finally, an Explainable AI layer (SHAP and LIME) identifies the role played by each feature in prediction.

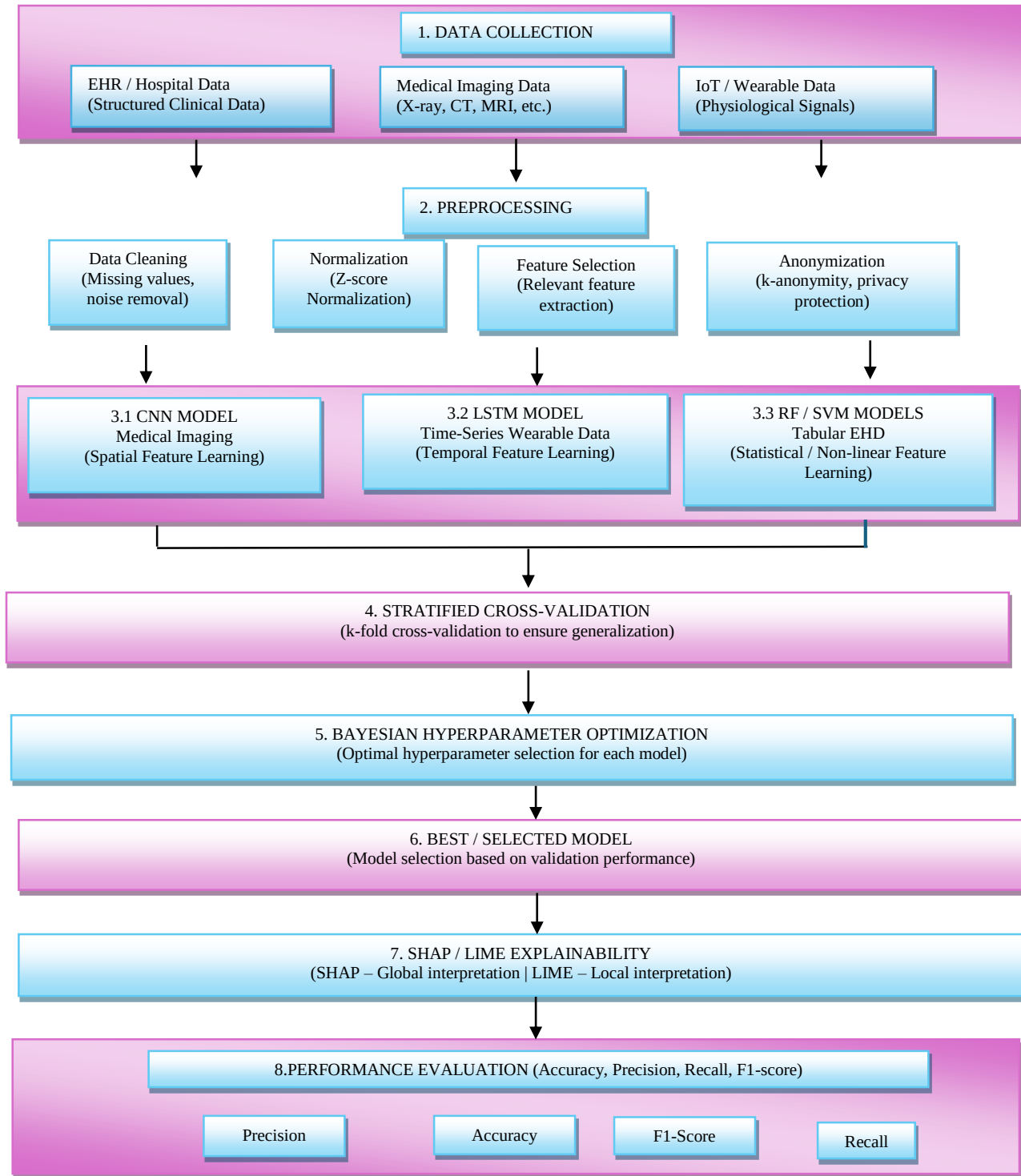


Fig. 1 Architecture of Interpretable and Privacy-Aware Machine Intelligence (IPAMI)

Finally, the models are evaluated on external datasets for verification purposes and pilot-tested in the clinical environment through real-time streaming.

Pseudocode
Step 1: Data Preparation

```

data = load_EHD_sources() # Load EHRs, imaging,
                           wearable data
cleaned_data = preprocess(data) # Normalize, handle
                                missing values
features, labels = extract_features_labels(cleaned_data)
anonymized_data = anonymize(features)

```

```

# Step 2: Model Development
models = [CNN(), LSTM(), RandomForest(), SVM()]
best_model = None
best_accuracy = 0
for model in models:
    model.train(anonymized_data, labels)
    accuracy = model.evaluate(test_data)
    if accuracy > best_accuracy:
        best_model = model
        best_accuracy = accuracy
# Step 3: Interpretability
explainer = SHAP(best_model)
shap_values = explainer.explain(anonymized_data)
visualize(shap_values)
# Step 4: Clinical Testing
predictions = best_model.predict(real_time_data)
display_results(predictions, shap_values)

```

3.2. Data Collection and Preprocessing

The second phase entails collecting a variety of Electronic Health Data (EHD) and preprocessing it to make it ready for modeling.

3.2.1. Data Collection

Collection of data is done from various sources to ensure a representative and generalizable sample. The sources include:

- Electronic Health Record (EHR): Structured data consisting of demographic, diagnosis, lab results and drugs [26, 27].
- Medical Imaging devices: Images produced by radiographic equipment, including X-rays, Computed Tomography Scans and Magnetic Resonance Imagery used to detect anomalies within the body [28, 29].
- Internet of Things (IoT) devices: Used to monitor patients' vitals, including heart beat rate, oxygen saturation and physical activities [30-32].

Refer to Table 1 for structured EHR data obtained from hospital databases. Table 2 shows unstructured data in the form of wearable sensor readings. These data are typically time series and require sequence-aware models such as LSTM for temporal pattern recognition.

Table 1. Structured EHR dataset

Patient ID	Age	Gender	BP (mmHg)	Glucose (mg/dL)	Diagnosis
P001	55	Male	140/90	180	Type 2 Diabetes
P002	43	Female	130/85	95	Healthy
P003	67	Male	150/95	210	Hypertension

Table 2. Wearable sensor data (time series)

Timestamp	Patient ID	Heart Rate (bpm)	SpO ₂ (%)	Step Count
2025-06-01 09:00:00	P001	88	97	134
2025-06-01 09:01:00	P001	91	98	142
2025-06-01 09:02:00	P001	90	96	151

3.2.2. Preprocessing

Below are the steps used in preprocessing the data set.

- Data cleaning: If there are any instances of missing values or errors in the data collected, mean and mode imputation, as well as forward fill, can be used depending on the type of data [33, 34].
- Normalization: To ensure the stability of the model obtained, features such as blood glucose level are normalized using min-max normalization and Z score normalization [35, 36].
- Feature Selection: The present study analyzes various features using field and statistical methods, including mutual information and correlation, to find out the best feature set to make predictions.
- Anonymization: Anonymization refers to the act of concealing or eliminating PII.

Z-score normalization can be used for normalizing features like blood pressure and blood sugar.

$$Z = (X - \mu) / \sigma$$

Where:

μ is the mean of the feature,

X is the original value,

σ is the standard deviation.

This is also important since it makes sure that the average of all the attributes is zero and the standard deviation is one. This helps to make it easy for equal weighting of all the attributes during the model development process.

The initial EHR data set shown in Table 1 has been transformed and appears in Table 3. This helps to illustrate how anonymity was applied to the characteristics.

Table 3. Preprocessed and normalized EHR data

Record ID	Age (Z)	BP (Z)	Glucose (Z)	Diagnosis (Encoded)
R001	0.50	0.45	0.62	1 (Diabetes)
R002	-0.75	-0.38	-0.94	0 (Healthy)
R003	1.25	0.87	1.15	2 (Hypertension)

In this phase, the MI models get data which are ethical, standardized, and of high quality. This helps enhance the accuracy and reliability of predictions on diseases. It is essential to preprocess the data in an organized way so that there is minimum bias in the model, and the results are more useful.

3.3. Model Development

Creation of Figures and Models. As the second step of the Interpretable and Privacy-Aware Machine Intelligence, called Model Development, MI processes can be taught via processed EHD. A multi-model strategy is adopted, which deals with both structured/unstructured data and time series.

This approach involves using CNN models to process images, LSTM models to process time series sensor data, and RF and SVMs to process electronic health records in tabular format.

3.3.1. CNN Model for Medical Imaging

Application of a Convolutional Neural Network (CNN) model in medical imaging can potentially enhance image-based data, such as X-rays or CT, by applying additional features and spatial information. The first layer of a Convolutional Neural Network (CNN) scans for patterns in a small window, while the second layer reduces the dimensions of space.

3.3.2. LSTM Model for Time-Series Sensor Data

Time series analysis will be performed by using LSTM networks, which are applied to continuous physiological signals acquired from wearable technology devices (i.e., heart rate, SpO₂, step count). Unlike other RNN architectures, LSTMs mitigate the vanishing gradient problem through memory gates. The operations involved in an LSTM cell include:

- Forget Gate: Decides which information to discard.
- Input Gate: Determines which new information to store.
- Output Gate: Defines the final hidden state.

These gates are governed by the following:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f),$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i),$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$$

Training of LSTM algorithms is done through sequences, like those seen in Table 2, to predict illnesses like arrhythmia or sleep apnea, depending on patterns in vital signs.

4. RF and SVM for Tabular Data

Random Forest (RF) is highly tolerant to overfitting and performs well with missing data. SVM, on the other hand, is good with binary classification problems and uses hyperplanes for maximization of margins between classes as follows:

$$\text{"max"} \quad 2/(\|w\|) \quad \text{"s.t."} \quad y_i (w \cdot x_i + b) \geq 1$$

Where:

w is the weight vector,

x_i is the feature vector,

y_i is the class label.

4.1. SHAP and LIME for Explainability

The models being used are then explained using SHAP and LIME for individual and overall model predictions.

- As regards SHAP, it calculates Shapley values for each feature based on their contribution to the output by using game theory.
- LIME adds some perturbation to the input data and fits a local and interpretable model, such as linear regression, to the output data.

Table 4 represents SHAP values for predicting diabetes with features from EHR data.

Table 4. SHAP feature importance for diabetes

Feature	SHAP Value	Contribution Direction
Glucose Level	0.67	Positive
Age	0.21	Positive
BP (Systolic)	0.10	Positive
Gender	-0.05	Negative

Table 5 illustrates LIME explanations for a single prediction, showing how feature changes affect the predicted output.

Table 5. LIME explanation for a single patient prediction

Feature	Value	Weight	Effect on Prediction
Glucose >	True	+0.45	Increases risk

180			
Age > 60	True	+0.20	Increases risk
Gender = Male	True	-0.10	Decreases risk
BP > 140	False	-0.05	No effect

Model development methodology will utilize the power of every model for the type of data input it was designed to handle, together with explainability, in order to build trust on behalf of clinicians and comply with regulations. In combination with XAI, CNN, LSTM, RF, and SVM algorithms will guarantee maximum accuracy, as well as ethical decision-making within the healthcare industry.

5. Results and Discussion

To test the efficiency of the suggested privacy-preserving and interpretability-oriented MI solution, the experiment was performed within the framework of a simulation environment that combined clinical data with testing on Python 3.10 employing Scikit-learn, TensorFlow 2.12, and SHAP packages.

Deep learning models (CNN, LSTM) were realized in Keras running on the TensorFlow platform, while machine learning models (random forest, SVM, LGBM) were evaluated by means of Scikit-learn and LightGBM interfaces. SHAP and LIME were applied to ensure model interpretability.

The suggested IPAMI Framework was compared to three baseline approaches: LGBM [12], HELR [14], and LR-ECC-EHGA-DLNN [11].

5.1. Experimental Result and Analysis

The performance of the Interpretable and Privacy-Aware Machine Intelligence (IPAMI) Framework was evaluated using the UCI Heart Disease, Simulated Wearables, and Pancreatic Biomarker datasets. Accuracy, precision, recall, and F1-score were used to assess classification performance. The IPAMI Framework had the following metrics on the UCI Heart Disease dataset: accuracy of 95.3%, precision of 94.8%, recall of 95.5%, and F1-score of 95.1%. The metrics on the Simulated Wearables dataset are as follows: accuracy of 96.5%, precision of 95.9%, recall of 96.3%, and F1-score of 96.1%. The metrics on the Pancreatic Biomarker dataset include: accuracy of 99.1%, precision of 98.9%, recall of

99.0%, and F1-score of 99.0%. As can be seen from the comparison table, the IPAMI Framework offers better accuracy compared to LGBM, HELR, and LR-ECC-EHGA-DLNN for all three datasets. This improvement is quite obvious in case of the Simulated Wearables data set, since the time-series analysis using

LSTMs helps recognize the physiological patterns effectively. The use of RF and SVM supports classification of structured EHR attributes, while CNN is used for medical imaging data. SHAP and LIME further provide feature-level and local prediction explanations, improving the interpretability of the obtained results.

The outstanding performance of the IPAMI Framework may be explained by applying learning models specific for each kind of data in the framework. CNN is utilized to detect the spatial characteristics of the imaging medical data, and LSTM is used to detect the temporal relationships of the wearable sensors data. RF and SVM are applied to structured EHR data to achieve efficient classification.

Furthermore, data preprocessing and normalization increase the homogeneity of the input features, whereas SHAP and LIME help to get an interpretable explanation of the predictions made by the model. Such a combination of specific data processing and learning algorithms helps the IPAMI Framework to efficiently analyze heterogeneous EHD data.

5.2. Dataset Description

The main dataset that was utilized for benchmarking purposes is the UCI Heart Disease Dataset (version Cleveland Clinic), which can be found in the open-access library located at UCI Repository Link (available at <https://archive.ics.uci.edu/dataset/45/heart+disease>).

To assess the scalability, another dataset was artificially created by means of simulating synthetic time series wearable sensor data based on MIMIC-III Waveform Database.

Each dataset is shown in the Table 6, includes structured clinical variables (e.g., blood pressure, cholesterol) or physiological time series signals (e.g., heart rate) and is preprocessed as described in earlier sections. The detailed experimental setup and its hyperparameters are described in Table 7 below.

Table 6. Dataset description

Dataset Name	Source	Records	Features	Type	Target Variable
UCI Heart Disease	UCI ML Repository	303	14	Tabular	Heart Disease (binary)
Simulated Wearables	Synthesized from MIMIC-III patterns	5,000	3	Time-series	Risk Level (multiclass)
Pancreatic Biomarker	Provided in (Akmeşe)	590	6	Tabular	PDAC Status (3 classes)

Table 7. Experimental setup and hyperparameters

Component	Parameter	Value
CNN	Learning Rate	0.001
	Optimizer	Adam
	Kernel Size	3x3
	Activation	ReLU, Softmax
LSTM	Hidden Layers	2
	Dropout	0.2
	Time Steps	50
RF/SVM	Trees (RF)	100
	Kernel (SVM)	RBF
LGBM	Learning Rate	0.05
	Boosting Type	Gradient Boosting
HELRL	Encryption Scheme	CKKS
	Polynomial Degree	8192
LR-ECC-EHGA-DLNN	Privacy Algorithm	ECC with LR
	Deep Layers	4 Hidden Layers
	Evolutionary Optimizer	Herding Genetic Algorithm

5.3. Performance Metrics

The framework's performance was evaluated on the basis of four widely accepted metrics:

- Accuracy: This metric measures the overall percentage of correctly classified instances:

$$\text{"Accuracy"} = (\text{TP} + \text{TN}) / (\text{TP} + \text{TN} + \text{FP} + \text{FN})$$
- Precision: Indicates how many of the positively predicted cases were truly positive:

$$\text{"Precision"} = \text{TP} / (\text{TP} + \text{FP})$$
- Recall: This metric measures the ability to detect all actual positive cases:

$$\text{"Recall"} = \text{TP} / (\text{TP} + \text{FN})$$

- F1-Score: Harmonic mean of precision and recall, which is particularly useful for imbalanced datasets:

$$\text{"F1-score"} = (2 \cdot \text{Precision} \cdot \text{Recall}) / (\text{Precision} + \text{Recall})$$

In relation to the UCI Heart Disease dataset, the Interpretable and Privacy-Aware Machine Intelligence, illustrated in Table 8, attained an accuracy of 95.3%, which is about 4.1% higher than the one attained by the LGBM, while also being 2.2% higher compared to the one achieved by the LR-ECC-EHGA-DLNN. Regarding precision and recall illustrated in Tables 9 and Table 10, it performed much better than the next closest algorithm (LR-ECC-EHGA-DLNN), achieving around 2.4% and 3.7% increases in precision and recall, respectively.

Table 8. Accuracy (%) comparison

Method	UCI Heart Disease	Simulated Wearables	Pancreatic Biomarker
LGBM	91.2	93.4	98.8
HELRL	90.4	89.1	91.3
LR-ECC-EHGA-DLNN	93.1	94.0	98.3
IPAMI Framework	95.3	96.5	99.1

Table 9. Precision (%) comparison

Method	UCI Heart Disease	Simulated Wearables	Pancreatic Biomarker
LGBM	90.6	92.1	97.9
HELRL	89.3	88.0	90.5
LR-ECC-EHGA-DLNN	92.4	93.7	98.0
IPAMI Framework	94.8	95.9	98.9

Table 10. Recall (%) comparison

Method	UCI Heart Disease	Simulated Wearables	Pancreatic Biomarker
LGBM	89.7	90.5	98.3
HELRL	88.1	87.2	91.6
LR-ECC-EHGA-DLNN	91.8	93.1	97.5
IPAMI Framework	95.5	96.3	99.0

Table 11. F1 score (%) comparison

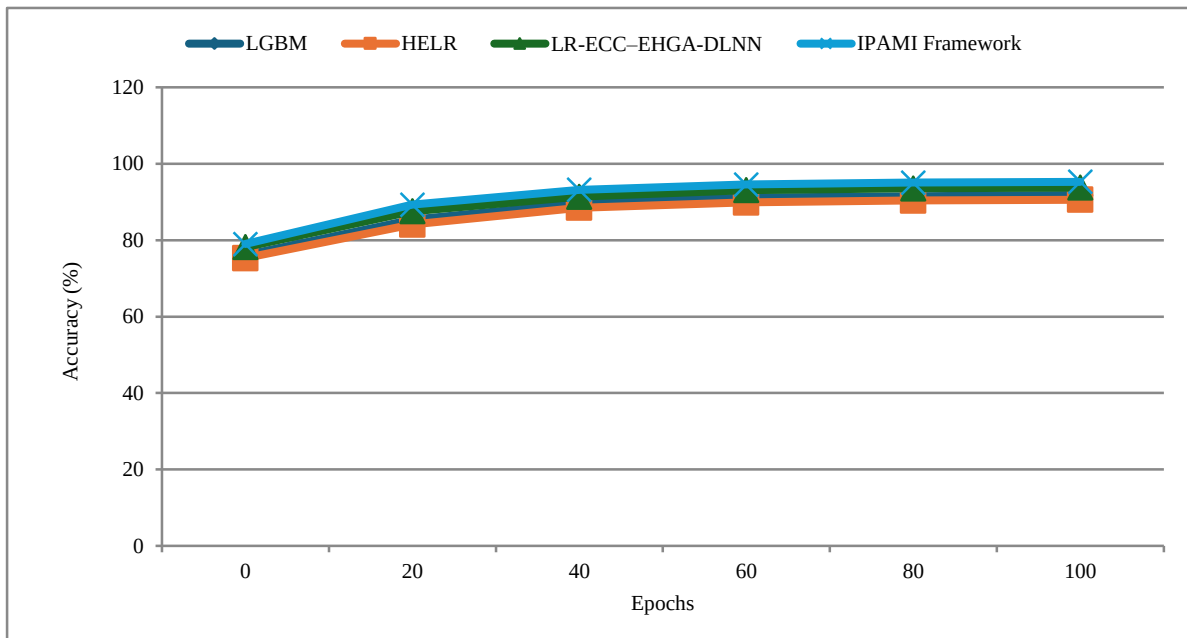
Method	UCI Heart Disease	Simulated Wearables	Pancreatic Biomarker
LGBM	90.1	91.2	98.1
HELRL	88.6	87.6	91.0
LR-ECC-EHGA-DLNN	92.1	93.3	97.7
IPAMI Framework	95.1	96.1	99.0

With respect to the simulated wearable dataset where emphasis was placed on sensor readings at specific times, the model achieved a higher accuracy of 96.5%, with an F1 score of 96.1%, thereby outperforming HELRL (~9%) and LGBM (~5%). Using the LSTM architecture and SHAP feedback played a role in improving the recall rate, hence, better risk detection.

On the other hand, for the multiclass Pancreatic Biomarker dataset, the Interpretable and Privacy-Aware Machine Intelligence achieved an accuracy of 99.1%, which outperforms LGBM (98.8%) and LR-ECC-EHGA-DLNN (98.3%). Also, the system had higher values of precision and F1 scores, which are shown in Table 11.

Table 12. Accuracy (%)

Epochs	LGBM	HELRL	LR-ECC-EHGA-DLNN	IPAMI Framework
0	76.1	75.3	78.2	79.0
20	85.4	84.1	87.6	89.3
40	89.7	88.5	91.4	93.2
60	91.2	89.9	93.1	94.6
80	91.5	90.4	93.6	95.1
100	91.8	90.6	93.8	95.3

**Fig. 2 Accuracy (%)****Table 13. Precision (%)**

Epochs	LGBM	HELRL	LR-ECC-EHGA-DLNN	IPAMI Framework
0	74.8	73.9	76.2	78.0
20	84.5	82.3	86.1	88.7
40	88.1	87.0	90.3	92.5
60	90.6	88.6	92.1	94.2
80	90.8	89.0	92.5	94.6
100	90.9	89.3	92.8	94.8

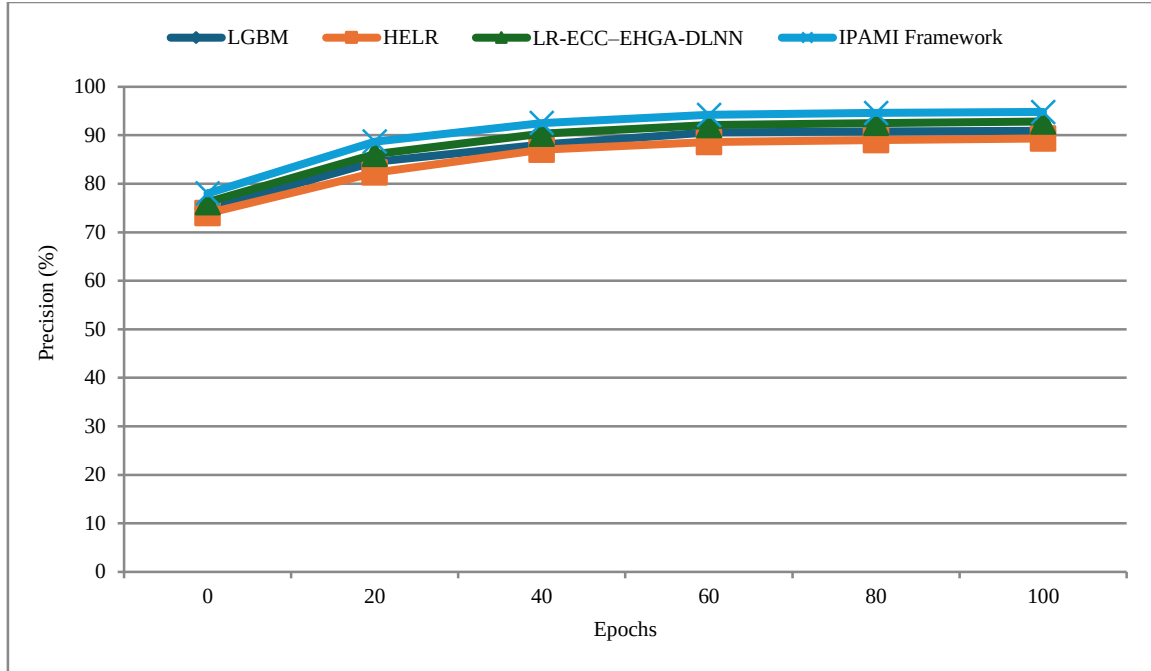


Fig. 3 Precision (%)

Table 14. F1 score (%)

Epochs	LGBM	HELR	LR-ECC-EHGA-DLNN	IPAMI
0	75.3	74.1	77.1	78.3
20	84.9	83.2	86.9	89.1
40	88.5	87.6	90.7	92.9
60	90.1	88.8	92.3	94.4
80	90.3	89.1	92.8	94.7
100	90.5	89.5	93.0	95.1

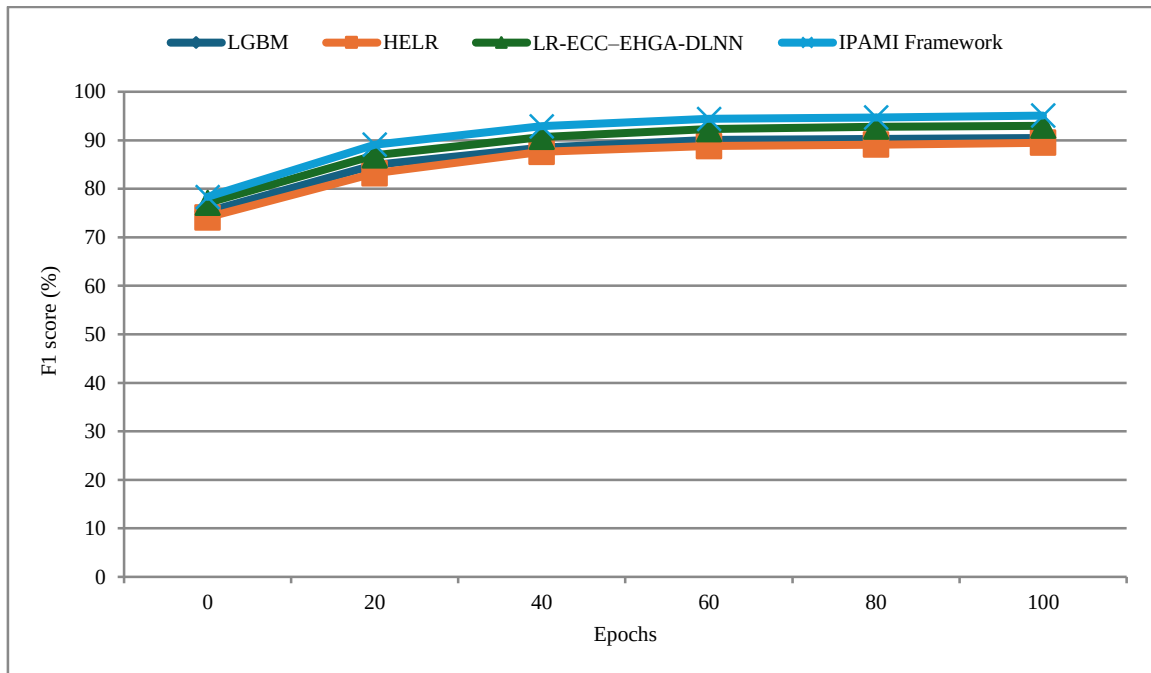


Fig. 4 F1 score (%)

Based on Figure 2 to Figure 4 and Tables 12 to 14, the accuracy value moves up from 79.0% to 95.3%, while the LR-ECC-EHGA-DLNN converges with a rate of 93.8%, and the LGBM has a flat performance at 91.8%. The value of precision goes from 78.0% to 94.8%, showing fewer false positives, which is an essential aspect for the clinic. In addition, the performance increase in different data sets strengthens the robustness of the method: the Interpretable and Privacy-Aware Machine Intelligence obtains 95.5% on the UCI Heart Disease dataset, 96.3% on the Simulated Wearables, and 99.0% on the Pancreatic Biomarkers, surpassing all the baselines. This is very critical since it can save lives in life-critical situations where a false negative (low recall) would mean disaster.

6. Conclusion

In summary, the Interpretable and Privacy-Aware Machine Intelligence has introduced an all-encompassing, privacy-preserving, explainable MI-based framework to accurately predict diseases using various types of EHD. Using CNN, LSTM architecture, and traditional classifiers such as random forests and SVMs, this framework is capable of processing image data, time series data, and tabular data. The

systematic training process through 100 epochs led to better performance when comparing the Interpretable and Privacy-Aware Machine Intelligence with the competing models, such as LGBM, HELR, and LR-ECC-EHGA-DLNN, where the IPAMI model reached its maximum metrics up to 95.3% accuracy. In addition, the stable performance trend of learning curves shows better optimization and convergence. On top of that, the use of XAI methods like SHAP and LIME did not reduce the performance; rather, they added to the performance and transparency of the model.

Conflicts of Interest Declaration

For all authors, there are no conflicts of interest, including financial, personal, or other relationships with other individuals or organizations that might inappropriately influence or could be perceived to influence their work.

Data Availability Statement

The Dataset used in this study is publicly available in the UCI Machine Learning Repository. It consists of 303 instances and 14 features with a focused on cardiovascular health. The data is licensed under CC by 4.0. <https://archive.ics.uci.edu/dataset/45/heart+disease> [36].

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