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CONTEMPORARY APPROACHES TO AUTOMATED FALL DETECTION SYSTEMS

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Abstract
It is observed that falls among senior citizens and patients with similar neurological disorders like epileptic seizures are very common these days. Therefore, falls are reported annually, which may lead to severe injuries. In certain cases, deaths are also reported, particularly when there is a lack of supervision or when the adults are residing alone in the UK or in European countries. To minimize these risks and enhance the independence of individuals, accurate fall detection systems have been proposed. These issues are addressed by presenting sensor based, IoT, ML, and DL based architecture by various authors. These systems employed classification techniques in order to classify fall and non fall events in real time. The data is cleaned by using bandpass filters and data preprocessing techniques. The authors used various classification models like SVM, KNN, 1DCNN, and 2DCNN along with the XAI techniques, which include LIME and SHAP. This paper generates a comprehensive review of the existing methodologies and highlights their pros and cons. Subsequent research of the existing studies of the past 5 years includes data security, exploration and development of systems that detect all seizure types, utilization of the advanced DL models, detection of falls in real time, and so much more. On the whole, this paper provides a comprehensive literature review that understands the existing systems, their challenges, and future directions, which helps to develop more reliable and efficient systems that would bring an evolution in the healthcare systems.

1. INTRODUCTION

1.1 Classical ML Approaches in the Healthcare Industry

Machine Learning (ML) and Artificial Intelligence (AI) bring innovation in the healthcare industry. AI plays an important role in early disease detection and prediction, which is unfamiliar to most of the healthcare professionals [4][5]. Because of the recent advancements in AI, Medical Imaging technology plays a crucial role in determining and highlighting the difference between tumor boundaries and healthy tissues [6] and also detects any other abnormality. AI algorithms help healthcare professionals to diagnose diseases precisely [7]. However, XAI techniques enhance the analyzability of the model predictions in the healthcare area, which assists in more precise machine predictions in

comparison to clinical predictions [8]. Likewise, ML techniques and algorithms are also widely used in precise disease detection and prediction. ML models like LSTM, CNN, and GRU; ML algorithms like RNN, CNN, KNN, RF, K-Means Clustering, and ANN are widely used for data collection and preprocessing operations, like data balancing, noise reduction, and feature selection; also, these algorithms and models are important for automatic and precise diagnosis.

1.2 Reasons for Fall Detection Among Senior Citizens

Furthermore, falls among older adults are a main concern nowadays. Sudden accidental falls in elderly people may cause some sort of severe injuries which may affect their mobility or may lead to sudden death [1]. Falls may also occur in young adults due to some neurological disorders like epileptic seizures. Numerous factors may lead to fall accidents; these factors may include the person's age, walking issues, sleep apnea, or any kind of neurological disorder [2] like Epileptic seizure (ES). Around the age of 65, about 28-35% experience a fall in a year, and elders around the age of 75 experience a fall about 32-42%; these statistics are given by Altman's in [3]. In 2015 there are over 55% of deaths reported in [3] were due to injuries caused by falls. In compliance with these challenges, the development of an automatic ML and AI-based fall detection and disease prediction system.

1.3 Solution-Based Approach for Fall Detection

Similarly, there are a lot of studies done to develop efficient and precise systems to detect falls among aged people. Cardio Vascular Disorder (CVD) is a major cause of death now a days that may cause fall in adults; In study [9], A system developed using Long Short Term Memory (LSTM) ML model which helps in the prediction of heart rate (HR), ECG signals and generates alarms in case of any abnormality, this system also provides self monitoring functionality to users so they can monitor their health status. A wearable sensor-based system developed in [2] to detect falls among older adults by generating alarms when a human body hits any hard surface. This system is developed by using Support Vector Machine (SVM) and Random Forest (RF) ML algorithms with average precision of 95%, 0.96%, and 0.98% in Non-Fall, Pre-Fall, Pre Fall and Fall. Likewise, some neurological disorders may lead to fall like ES. The study [11] proposed an ES detection framework that is EEG based consists of Convolutional Neural Network (CNN), Gated Recurrent Unit (GRU), and LSTM ML models, which basically assist in getting a precise diagnosis. XAI techniques like Shapley are used to get precise results and accurate medical diagnosis. Various sensors are used in the detection and prediction of epilepsy causes fall in adults. Also, to detect the person's location, a GSM and GPS module are used to develop an efficient system [12]. In the same way, detection of falls in older adults is a current research topic nowadays. There are many recent studies done on fall detection, and there are systems developed based on fall detection. For the assurance of fall and non fall events, Group Teaching Optimization Algorithm (GTOA) with Stacked Auto Encoder (SAE) was used in [13]. To detect fall events in senior citizens, deep learning models are used, which involve feature extraction, preprocessing, and parameter optimization. To train models, limited datasets are available in this scenario, such as KFall, SisFall, URFD, UP fall, and MCF. Figure 1 shows the result analysis of the DL model on the MCF dataset.

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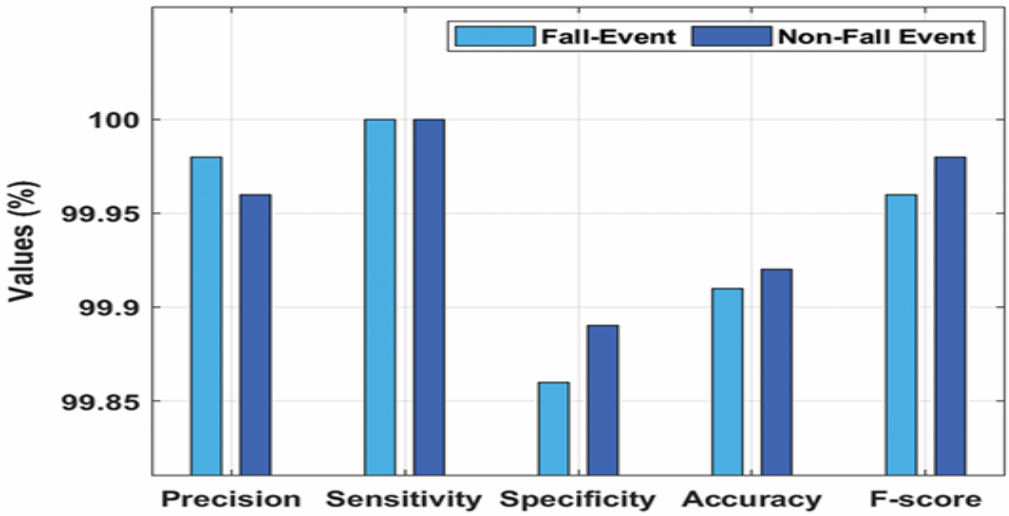


Figure SEQ Figure * ARABIC 1 Result evaluation of DL model on MCF dataset [13]

There is a lot of work done in developing fall detection systems. In the same way, the main concern here is that the development of the systems involves the precise detection and prediction of the fall occur before hand.

2. BACKGROUND

Recent studies have shown that due to accidental falls, there has been a hike in death rates of senior citizens. There are multiple fall detection systems (FDS) that are developed by the integration of Machine learning (ML), Deep Learning (DL), Artificial Neural Network (ANN), and Explainable AI (XAI), which includes SHAP and LIME techniques. There are several biologically inspired algorithms used in developing these systems which include: spike statistical flower pollination algorithm, convolutional neural network (CNN), Salp swarm optimization (SSO) algorithm, Adaptive Particle swarm and Grey Wolf Optimization (APGWO) algorithm; Other commonly used known algorithms are Random Forest (RF), Support vector machine (SVM), K nearest neighbors (KNN), while many others also exist. By using these algorithms, developed systems have achieved accuracy from about 72.69% to 99.76%. The following shows the detailed methodologies, technologies, limitations, and the research gaps by every author.

2.1 Detection of Epileptic Seizures

Tang et al. (2021) proposed Seizure detection using wearable sensors and machine learning: Setting a benchmark. The detection of epileptic seizures is through wrist- and ankle worn multi signal biosensors [sensors collected information: Body Temperature, electrodermal activity, blood volume pulse], EDA sensor, ACC (accelerometry); the data is collected from patients admitted to the hospital. The cons of this proposed work are that the Interference in the consistency of the signals (like each part of the body generates different signals), and most seizure types still need to be investigated. The future work recommends considering clinical chronoepileptological variables (seizure duration, etiology/ syndrome), alternative data balancing, pre and post processing, fusion, ensemble learning methods [25].

Idrees et al. (2022) proposed an Edge Fog Computing Enabled Lossless EEG Data Compression with Epileptic Seizure Detection in IoMT Networks. They used a method of Epilepsy Seizure Detector based Naïve Bayes algorithm (ESDNB) and KCHE, which surpasses other

algorithms in terms of accuracy by achieving 99.53% up to 99.99% accuracy on Bonn University Dataset [20].

An IoT based monitoring system is developed by Hassan et al. (2022) for epileptic patients. The data collection is through ECG, EMG, accelerometer 3 axes (fall detection), Dallas: DS18B20 sensor (body temperature signals monitoring), sound detection sensor. The accuracies reported in this work are Body Temperature: 98.90%, Heart Rate Monitoring: 95.49%, Muscle Spasm: 83.0%, Fall Detection: 87.21%. The cons of this proposed work are that this Requires additional testing on real world scenarios. The future work recommends the FISIoT framework to measure different categories of patients, accurate monitoring, false alarm detection, and control and monitor all random occurrences [27].

An IoT Smart Cane Device is developed by Adebiyi et al. (2022) for Abnormal Gait and Tremor Detection in the Elderly Ambulatory Behavior. To develop a smart cane device Low pass filter, ML algorithms (LDA, Isolation Forest, one Class SVM), feature extraction (SMA), energy feature (STFT), dimension reduction with PCA, and classification using LDA are used and score of 98% accuracy. The cons of this proposed work are that the device is prone to type 2 errors. The future work recommends an intermediate sensor that can also be embedded to differentiate between when the cane is asleep or when an accidental fall occurs, which reduces type 2 errors [23].

Yedurkar et al. (2024) proposed an IoT based novel hybrid seizure detection approach for Epileptic Monitoring. EEG sensors were used to detect epileptic seizures. This approach includes MRAF based preprocessing, feature extraction by SS-CSV, feature selection, and classification by 3 classifiers: SVM, KNN, and 2D CNN. The 98.48% accuracy is achieved in detecting seizures by the TUH EEG (an epileptic EEG multichannel benchmark dataset); a dataset obtained from the hospital in the western Indian city of Pune. The cons of this proposed work are that there is no examination of other seizure types. The future work recommends the Real time seizure localization for epilepsy [21].

Basavaiah et al. (2024) proposed an efficient approach of epilepsy seizure alert system using IoT and machine learning. No publicly available dataset was used here, although the data were collected from epilepsy patients admitted to the private hospital for pre surgical evaluation; the ECG sensor AD8232 included: 10 patients; 5 males and 5 Females, 55 seizure types, 621 hours of recordings. Their work reported accuracies of 95.26%, 92.93%, and 93.68% by CNN, RF, and LR, respectively. The future work recommends enhancing ML models' accuracy through the integration of blockchain technology [12].

Khan et al. (2025) developed a system to detect epileptic seizures (ES) by using an EEG sensor to detect seizures and an XAI approach. XAI approach includes Local Interpretable Model Agnostic Explanations (LIME) and Shapley Additive Explanation (SHAP). LIME is used for the Random Forest (RF) classifier, and SHAP is used for dependency analysis using dependency graphs. This system helps in the early diagnosis of epilepsy and also helps healthcare professionals in early treatment plans for epilepsy patients. The algorithms SVM, KNN, and RF are used to train the system on the CHB-MIT scalp EEG dataset (49 EEG recordings, 23 subjects; 21 having epilepsy + 2 having healthy controls). This proposed system achieved accuracies around 97.26%, 72.69%, and 99.89% by using algorithms SVM, KNN, and RF, respectively. This system can be improved by developing attention based models for capturing details of the EEG data [8]

By using a Hybrid CNN-LSTM-GRU Model with Data Balancing and XAI Integration, Torkey et al. (2025) proposed a system for seizure detection in medical IoT. The epileptic seizure is detected through the EEG signals. The method used for the proposed work is data acquisition and data preprocessing, which includes minmax normalization, SMOTE, and XAI via SHAP. The Epileptic seizure recognition dataset (Normal activity = 9200, seizure activity = 2300, 11,500 samples each with 178 features) is used to train

the model and achieves 99.13% accuracy. The cons of this proposed work are the absence of external evaluation on diverse datasets, limited generalizability, synthetic data bias, management of sensitive medical data, high computational demands, scalability, and integration. The future work recommends enhancing the model robustness and to enhance the generalizability [11].

Table 1. Summary of reviewed studies on epileptic seizure detection

Sr.	Author/Year	Method Used	Dataset	Accuracy	Limitation
1.	Khan et al. (2025)	Preprocessing by FIR Band Pass filter, statistical feature extraction, Classification by SVM + KNN + RF, XAI via LIME + SHAP	CHB-MIT scalp EEG dataset (49 EEG recordings, 23 subjects; 21 having epilepsy + 2 having healthy controls)	SVM (97.26%), KNN (72.69%), RF (99.89%)	-
2.	Torkey et al. (2025)	Data acquisition, preprocessing includes: minmax normalization + SMOTE, XAI via SHAP	Epileptic seizure recognition dataset (Normal activity = 9200, seizure activity = 2300, 11,500 samples each with 178 features)	99.13%	Absence of external evaluation on diverse datasets, limited generalizability, synthetic data bias, management of the sensitive medical data, high computational demands, scalability and integration
3.	Idrees et al. (2022)	KCHE, ESDNB	Bonn University Dataset	99.53% up to 99.99%	KCHE has less compression power
4.	Yedurkar et al. (2024)	MRAF based preprocessing, feature extraction by SS-CSV, feature selection, Classification by 3 classifiers: SVM + KNN + 2D CNN	TUH EEG (an epileptic EEG multichannel benchmark dataset), Dataset obtained from the hospital in the western Indian city of Pune	98.48%	No examination of other seizure types
5.	Adebiyi et al. (2022)	Low pass filter, ML algorithms (LDA, isolation forest, one Class SVM), feature extraction (SMA), energy feature (STFT), dimension reduction with PCA,	Dataset is not mentioned here	98%	Prone to type 2 error

		classification using LDA			
6.	Tang et al. (2021)	1D CNN, algorithms (1 = specific ML model for individual seizure types, 2 = generalized ML model for all seizure types)	Dataset is not mentioned here; data collected from patients admitted to the hospital	AUC-ROC = 0.957	No proper dataset used here; interference in the consistency of the signals (like each part of the body generates different signals). Most of the seizure types are not investigated here.
7.	Hassan et al. (2022)	Field epilepsy study, Fuzzy logic simulations	Dataset is not mentioned here	**Body Temperature:** 98.90%, **Heart Rate Monitoring:** 95.49%, **Muscle Spasm:** 83.0%, **Fall Detection:** 87.21%	No public dataset used here.
8.	Basavaiah et al. (2024)	Signal processing, ML algorithms (CNN, RF, LR)	No publicly available dataset used here (the data is collected from the epilepsy patients admitted to the private hospital for pre surgical evaluation, ECG sensor AD8232, including: 10 patients; 5 males + 5 Females, 55 seizure types, 621 hours of recordings)	CNN (95.26%), RF (92.93%), LR (93.68%)	Current models are not optimally trained; this proposed system has no data security mechanism.

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2.2 Monitoring Fall Detection Systems

Al-Kababji et al. (2021) proposed an IoT based framework for remote fall monitoring. There is a Utilization of training datasets, feature extraction algorithms, CWT, SVM, SMA (signal magnitude area), Signal Energy (SE), and ML classification algorithms (KNN, ENN, BDT, VM). UniMiB-SHAR dataset is used; 5 folds (70/30) train/test ratio (KNN = 96.23%, ENN = 97.68%, BDT = 94.20, VM = 97.68%) and 10 folds (90/10)

train/test ratio (KNN = 99.09%, ENN = 99.15%, BDT = 96.70, VM = 99.19%). Moreover, UniMiB-SHAR contains 11,771 records, of which ADL: 7,579 and Falls: 4,192. The cons of this proposed work are limited battery charge and Discomfort in wearing WSDs. The future work recommends designing sensors with long battery lives use multiple sensors (like if one is on charge, the other one can be used) [16].

By using ML classifiers, i.e., LR, DT, KNN, NB, SVM, RF, and MLP, Le et al. (2021) used a feature selection approach; An Adaptive Particle Swarm and Grey Wolf Optimization (APGWO) is for fall detection. This proposed work achieves 99% accuracy on the UP Fall dataset. For future work, the recommendations of the authors are the optimization of the parameters for the feature selection method and fine tuning the MLP structure [3].

For smart home care, Vaiyapuri et al. (2021) proposed an IoT and DL based elderly fall detection model. SSO and SSOA-VAE were used to train the IMEFDODCNN model and SqueezeNet model, which were used for the feature extraction technique on the datasets MCFD and URFD achieved accuracies 99.76%, and 99.57%, respectively. The proposed framework has several limitations, like poor performance on low quality videos, class imbalance in URFD (74 frames = fall event, 240 frames = non fall events), and no real time deployment testing. Likewise, the future work recommendations mentioned by the authors are that the performance of the model can be improved by the use of advanced DL models for the classification process, and development of a scalable and robust version of the model for the real time fall detection process specially from low quality videos [18].

By using DL and wearable sensors, Jain et al. (2022) proposed a Novel feature extraction method for a pre-impact fall detection system. The system uses an ensemble of LSTM and CNN models called FallNet. The proposed work is evaluated on well known publicly available datasets named SiSFall and KFall. The overall accuracy achieved by the system is 97.52%. The limitation of the system is that the microcontrollers and sensors are not evaluated, mimics falls, not actual falls; all the subjects are healthy and young, not senior citizens; SiSFall and KFall are the emulated datasets of young and healthy subjects, not tested on pathological gait; no deployment on microcontrollers and sensor networks. Moreover, the recommended future directions by the authors are to build a low-cost pre-impact FDS using a microcontroller (nano BLE sense and tinyML framework), test the efficiency of FallNet on humanoid fall data, pathological gait data, and real world fall data [15].

Anitha et al. (2022) proposed a Vision Based Real Time Monitoring System for Elderly Fall Event Detection Using Deep Learning. The methods that are used to develop a system are data preprocessing, Spatial feature extraction based on MobileNet + GRU, classification process based on SAE, parameter tuning process, and performance validation. The group teaching optimization algorithm (GTOA), stacked autoencoder (SAE), RNN, and CNN were used to train the VEFD DL model on MCF and URFD datasets, which reports 99.92% accuracy. The cons of this proposed work are that there are small datasets: URFD (314 frames; 74 = fall events, 240 = no fall events) and MCF (192 videos: 96 = fall, 96 = regular events). The future work recommends an enhancement in the performance of the VEFED DL model by an advanced DL architecture layer with a class attention layer [13].

A wearable sensor based fall detection system is proposed by Gangadhar et al. (2025) for elderly care using ensemble ML techniques. The SVM and RF algorithms are evaluated on the KFall dataset. For fall detection in senior citizens, gyroscope and accelerometer sensors are used here. This proposed solution helps to predict falls before it actually happens. The system achieves accuracy of 95%, 96%, and 98% on non-fall events, pre fall, and fall events, respectively. This enhances the quality of life of senior citizens by generating warning alarms and actions. The limitation here is that the dataset includes only

younger adults, but the proposed research is about fall detection in senior citizens [2].

Table 2. Summary of reviewed studies on fall detection and monitoring systems

Sr.	Author/Year	Method Used	Dataset	Accuracy	Limitation
1.	Gangadhar et al. (2025)	RF, SVM	KFall	Non Fall (95%), Pre Fall (96%), Fall (98%)	The dataset includes young people only but the target is senior citizens
2.	Le et al. (2021)	Feature selection (APGWO), classification by using 7 classifiers (LR, DT, KNN, NB, SVM, RF, MLP)	UP-fall detection dataset	99%	Feature selection parameter + MLP is not optimized, included only indoor environment
3.	Jain et al. (2022)	CNN, LSTM, Automatic feature extraction, Transitional Window (Tw), FallNet (ensemble of CNN +LSTM)	SisFall, KFall	97.52%	mimics falls only, no actual falls, all the subjects are healthy and young not the senior citizens, SisFall and KFall are the emulated datasets of young and healthy subjects, not tested on pathological gait, no deployment on microcontrollers and sensor networks
4.	Vaiyapuri et al. (2021)	Preprocessing (augmentation, resizing, min max normalization), SqueezeNet, SSO algotithm, SSOA-VAE classifier	URFD, Multiple cameras fall dataset (MCFD)	MCFD = 99.76% URFD = 99.57%	Poor performance on low quality videos, class imbalance in URFD (74 frames = fall event, 240 frames = non fall events), no real time deployment testing
5.	Anitha et al. (2022)	Data preprocessing, Spatial feature extraction based on MobileNet + GRU, classification process based on SAE, parameter tuning process, performance	MCF, URFD	99.92%	Small datasets: URFD (314 frames; 74 = fall events, 240 = no fall events) + MCF (192 videos: 96 = fall, 96 = regular events)

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		validation			
6.	Al-Kababji et al. (2021)	Utilization of training datasets, feature extraction algorithms, CWT, SVM, SMA (signal magnitude area), Signal Energy (SE), ML classification algorithm (KNN, ENN, BDT, VM)	UniMiB-SHAR (11,771 records out of which ADL: 7,579 + Falls: 4,192)	UniMiB-SHAR dataset: 5 folds (70/30) train/test ratio (KNN = 96.23%, ENN = 97.68%, BDT = 94.20, VM = 97.68%) + 10 folds (90/10) train/test ratio (KNN = 99.09%, ENN = 99.15%, BDT = 96.70, VM = 99.19%)	Limited battery charge, Discomfort in wearing WSDs

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2.3 Systems Addressing Cardiovascular Disorders

Tamilselvi et al. (2018) proposed A wearable device for fall detection and heart stroke prediction using IoT and machine learning. The multi sensor fusion includes a heart rate sensor, accelerometers, Pulse Sensor, temperature sensors, Humidity sensor, Pressure sensors, optical sensor (measures heart rate), acceleration sensors (detects abnormalities), IoT, ML pipeline method used for this work. The cons of this proposed work are that there is no dataset mentioned here, no accuracy metric used here, and no proper name of the ML algorithms used here; they just mention an unsupervised ML algorithm [17].

A wearable sensor developed for arrhythmia detection by Farooq et al. (2021) using ML classification. In case of any abnormality in cardiac health, the proposed work provides a functionality for automated appointments with cardiac professionals. ECG sensor is used in arrhythmia detection through which data is collected; Arduino UNO is used for signal processing in LabVIEW by using a morphological filter to remove noise from the ECG signal. For this study, data is only collected from the 3 patients (M1 45 yrs, M2 25 yrs, M3 35 yrs. Data collection is over 14 days. They did not use any evaluation metrics to show the accuracy of their work, and they used an extremely small dataset [10].

Choi et al. (2021) proposed ML Based Elderly Stroke Monitoring System Using Electroencephalography Vital Signals. They used method Raw EEG collection, data preprocessing, feature extraction via FFT, feature selection via CFS, ML classification includes algorithm (FFT, RF, Z-score normalization, C4.5 DT, C5.0 DT, NB, MLP, LR, two class SVM, C&RT (classification and regression tree), classification and regression tree, and QUEST) where the system achieves 92.51% accuracy on CV dataset (5 Fold CV, 10 Fold CV, 20 Fold CV). The future work recommends the Detection and prediction of other diseases like heart and cancer [22].

Kumar et al. (2023) proposed Flamingo Optimization Based Deep Convolutional Neural Network for IoT Based Arrhythmia Classification. Here, ECG sensors are used in arrhythmia detection. The authors collected data from the MIT-BIH dataset (includes men and women aged >22). Moreover, this proposed work includes data preprocessing using a standard scalar transform, classification via DCCNN, and hyperparameter optimization using the Flamingo optimization algorithm, which achieves 98.5% accuracy. In their work, there is no clinical deployment [19].

Cañón-Clavijo et al. (2023) proposed IoT Based System for Heart Monitoring and Arrhythmia Detection Using Machine Learning. The Polar H10 heart sensor and ECG sensor are used to collect data like BP, HR, etc. This system uses RF, KNN, CNN, Fuzzy Logic algorithm to train model on MIT-BIH-Arrhythmia dataset has 5 classes (N = normal beat, S = supraventricular premature beat, V = premature ventricular contraction, F = fusion of ventricular and normal beat, Q = unclassifable beat) evaluates RF (N = 93%, Q = 97%), KNN (V: 94%, F: 81%, S: 82%), CNN (N: 83%, S: 48%, V: 61%). The cons of this proposed work are that the CNN is not correctly detecting S and V type arrhythmias, RF does not perform well in comparison to CNN, KNN performs well on F class arrhythmias, and no single algorithm performs well on all classes [26].

A wearable device is developed for heart rate (HR) monitoring and Fall Detection (FD) by Nguyen et al. (2024) using ML to analyze and detect cardiovascular conditions at their earliest. For this purpose, they used an accelerometer and ADXL345 accelerometer sensors for detecting falls. The LSTM, including a prediction model and an autoencoder used, and the proposed approach achieves 94% accuracy. Here, there is no use of proper publicly available datasets. The limitation of the proposed approach is that the prediction of potential risks is 3 sec ahead from the current time; it is too short in case of serious health issues; predict abnormalities in a longer time [9].

An intelligent framework is developed by Rajpoot et al. (2025) for real-time heart stroke monitoring and early detection using ML models named RF and ANN. The framework consists of 2 layers, i.e., the cyber layer and the physical layer. The data preprocessing pipeline includes: feature selection, data normalization, data cleaning, model training, real time alert generation. The ML algorithms used in building this framework are: RF, DT, LR, and SVM. This proposed framework achieves 95.57% accuracy. For future direction, the authors recommended the Incorporation of DL models; CNN & LSTM, cloud and edge computing for low latency processing [14].

Table 3. Summary of reviewed studies on cardiovascular disorder monitoring

Sr.	Author/Year	Method Used	Dataset	Accuracy	Limitation
1.	Nguyen et al. (2024)	LSTM (Prediction model + Autoencoder)	Dataset is not mentioned here	94%	The prediction of potential risks is 3 sec ahead from the current time, which is too short in case of serious health issues, like predicting abnormalities over a longer time.
2.	Rajpoot et al.	CPS Framework based	Dataset is not	95.7%	No DL models used

	(2025)	on 2 layers (physical + cyber), ML models (RF + ANN), Data preprocessing pipeline (feature selection, data normalization, data cleaning, model training, real-time alert generation)	mentioned here		here like CNN & LSTM, latency concerns, no edge/cloud optimization.
3.	Kumar et al. (2023)	Data collection, preprocessing using standard scalar transform, classification via DCNN, hyperparameter optimization using Flamingo optimization algorithm	MIT-BIH dataset (includes men and women aged >22	98.5%	No clinical deployment
4.	Farooq et al. (2021)	Data collection through ECG sensor + Arduino UNO, signal processing in LabVIEW using a morphological filter to remove noise from the ECG signal, ML classifier: K-Means Clustering, IoT communication	Self collected dataset includes 3 patients: M1 45 yrs, M2 25 yrs, M3 35 yrs. Data collection is over 14 days.	No accuracy metric used here	Oversimplified data upload, extremely small dataset because only 3 patients were included
5.	Choi et al. (2021)	Raw EEG collection, data preprocessing, feature extraction via FFT, feature selection via CFS, ML classification includes algorithm (FFT, RF, Z-score normalization, C4.5 DT, C5.0 DT, NB, MLP, LR, two-class SVM, C&RT (classification and regression tree), classification and regression tree, and	CV dataset (5 Fold CV, 10 Fold CV, 20 Fold CV)	92.51%	-

		QUEST)			
6.	Cañón-Clavijo et al. (2023)	CNN, RF, KNN, fuzzy logic algorithm	MIT-BIH-Arrhythmia dataset has 5 classes (**N** = normal beat, **S** = supraventricular premature beat, **V** = premature ventricular contraction, **F** = fusion of ventricular and normal beat, **Q** = unclassifable beat)	**RF** (N = 93% Q = 97%), KNN (V: 94%, F: 81%, S: 82%), **CNN** (N: 83%, S: 48%, V: 61%)	CNN is not correctly detecting S and V type arrhythmias; RF does not perform well in comparison to CNN; KNN performs well on F class arrhythmias. No single algorithm performs well on all classes.
7.	Tamilselvi et al. (2018)	Multi sensor fusion, IoT, ML pipeline	Dataset is not mentioned here	No accuracy metric used here	No dataset mentioned here, no accuracy metric used here, no proper name of the ML algorithm used here

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2.4 Systems for Identification of Alzheimer Patients

For senile dementia patients, Wang et al. (2022) proposed an intelligent medical system based on a computer IoT framework with 5G to be applied in home care. The framework consists of smart wearable technology, Multi sensor indoor deployment, and FIR digital filtering. A self collected dataset is used for this proposed work, including a clinical study of 64 elderly senile dementia patients (35 males, 29 Females of 60 to 84years). The accuracies achieved in Behavioral feature extraction and Correct behavior recognition are 74.59% to 98.33%, and >98.5%, respectively. The limitation of this work is that the author included fewer samples, only tested the network backhaul effect for temperature data, and didn't further analyze other indicators. Likewise, the future direction recommended by the author is to add more indicators and more data for the detection [28].

Table 4. Summary of reviewed studies on dementia and Alzheimer patient monitoring

Sr.	Author / Year	Method Used	Dataset	Accuracy	Limitation
1.	Wang et al. (2022)	IoT framework with 5G, smart wearable technology, multi-sensor indoor deployment, FIR digital filtering, clinical study of 64 dementia patients	Self-collected clinical dataset of 64 elderly senile dementia patients (35 males, 29 females, aged 60-84 years)	Behavioural feature extraction: 74.59% - 98.33% Correct behaviour recognition: >98.5%	Few samples included; network backhaul tested only for temperature data; other signals such as ECG were not verified for transmission accuracy

2.5 Ascertainment of Diabetic and Hypertension Patients

Chatrati et al. (2022) proposed a smart home health monitoring system for predicting type 2 diabetes and hypertension. For the type 2 diabetes and hypertension prediction system used methods, Conditional decision making to predict the BP, SVM for the prediction of higher accuracy in diabetes prediction (diastolic BP and glucose). For this, the Pima Indians Diabetes Database (attributes: Pregnancies, Glucose, blood pressure, skin thickness, Insulin, Age, Outcome; 1 = Diabetic + 0 = Non Diabetic) is used and overall achieves 75% accurate results [24].

Table 5. Summary of reviewed studies on diabetes and hypertension prediction

Sr.	Author / Year	Method Used	Dataset	Accuracy	Limitation
1.	Chatrati et al. (2022)	Conditional decision making to predict BP; SVM for higher-accuracy diabetes prediction (diastolic BP + glucose)	Pima Indians Diabetes Database (attributes: Pregnancies, Glucose, Blood Pressure, Skin Thickness, Insulin, BMI, DiabetesPedigreeFunction, Age, Outcome; 1 = Diabetic, 0 = Non-Diabetic)	75%	Raw dataset requires processing before it is given to the model; manual data entry only

3. METHODOLOGIES

3.1 Classifiers Incorporated for Epileptic Seizure Detection

Tang et al. (2021) monitored epilepsy patients through wearable sensors, which were placed on either wrists or ankles. The sensors collected data like Body Temperature (BT), Electrodermal Activity, and Accelerometry (ACC), which gives Blood Volume Pulse (BVP). To balance the raw data under sampling is employed, and a CNN is used to classify the raw data. The data that is collected from the patients are trained and evaluated on two ML algorithms, where Algorithm 1 is a specific ML model for individual seizure type, and Algorithm 2 is a generalized ML model for all seizure types [25].

Idrees et al. (2022) used a hybrid approach of KCHE and ESDNB. K means Clustering and Huffman Encoding (KCHE) is utilized to reduce the amount of data sent from the edge gateway to the fog gateway by using lossless EEG data compression, and the Epileptic Seizure Detector Based Naïve Bayes (ESDNB) algorithm is utilized to take decision at the fog gateway, where the decision is based on the situation of the epileptic patient. By using the Bonn University Dataset, ESDNB achieves accuracy from about 99.53% to 99.99% [25].

Hassan et al. (2022) focuses on an epilepsy type named "Grand Mal Epilepsy Tonic Clonic (GTC) seizure". A field survey was conducted in three clinics (Nairobi, Kenya) to monitor the actual behavior of the epilepsy patients (51% male, 49% female), which is then monitored through the system. NodeMCU ESP32 reads the data from the sensors, and then the data is converted into digital format. The data is received by the UDP (User Datagram Protocol) and is then classified by FLC (fuzzy logic controller). Fuzzy Logic (FL) pre analyze the data and also helps in decision making process of seizure detection; if a seizure is detected, then a

notification is sent to the relatives and related health care professional [27].

A multichannel classification method is proposed by Yedurkar et al. (2024). The epileptic EEG data is preprocessed by using Multi Resolution Based Adaptive Filtering (MRAF). The features are then extracted by SS-CSV from the MRAF processed signals include: spike derived features, statistical based features, critical spectral verge, combinative based best feature selection, and classification. The authors use three classifiers: SVM, CNN, and KNN. TUH EEG, a multichannel benchmark dataset, is utilized for the evaluation of the performance of the proposed approach [21].

For EEG signal processing, the CHB-MIT scalp EEG dataset is used, which contains recordings of pediatric patients with some neurological disorders. For the optimization of the quality of EEG data, Khan et al. (2024) uses a preprocessing technique which is involved in the application of the band pass filter and epoch segmentation. The bandpass filter is used to eliminate noise and other artifacts. The authors used three types of classifiers, i.e., SVM, which is an ML algorithm to perform classification tasks; KNN handles multiclass and binary classification tasks, and RF is an ensemble learning algorithm used to make predictions by combining multiple decision trees to achieve better accuracy for the epileptic seizure detection system. Moreover, to enhance the interpretability of the models, XAI techniques, including LIME and SHAP, were integrated into the system. However, out of the listed three classifiers, RF surpasses both SVM (97.26%) and KNN (72.69%) by achieving 99.89% accuracy [8].

Basavaiah et al. (2024) proposed a system that uses sensors, GPS, and a GSM module to detect and predict epilepsy patients. The data is collected from different sensors, features are extracted from the sensor data (pulse rate sensor, temperature sensor, ECG sensor, tilt sensor, vibration sensor), and then the system predicts whether a fall has occurred or not. If the fall is detected, then a notification is sent to the guardian or to the caretaker along with the patient's location by using a GPS module. There is an integration of ML algorithms to examine the accurate diagnosis from the sensor data. ML algorithms CNN, RF, and LR achieve accuracies 95.26%, 92.93%, and 93.68%, respectively [12].

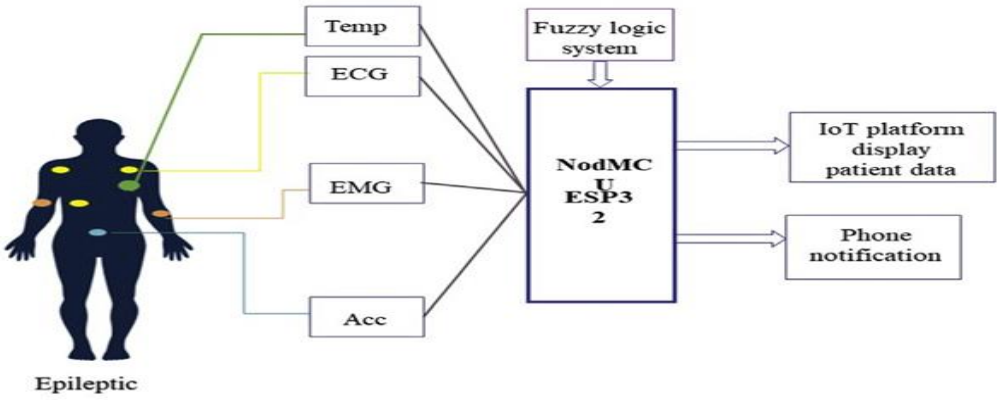


Figure 2. ES monitoring system using fuzzy logic [27]

3.2 Ensemble Machine Learning Based Frameworks

Farooq et al. (2021) uses LabView IV, where ECG waveform is monitored, various parameters are extracted, and the classification of these parameters (healthy, unhealthy, not defined) is done by utilizing K-Means Clustering, which is an ML algorithm. The data collection is done by getting data from 3 patients labeled as M1 (45 years), M2 (25 years), M3 (35 years) [10].

Chatrati et al. (2022) proposed a system based on an ML classification approach. For the detection

and prediction of diabetes, the Pima Indians Diabetes dataset is utilized, which includes different attributes like pregnancies, glucose, and BP; this is a raw dataset that requires preprocessing before it is given to the model. The feature engineering process is utilized to extract accurate features that contribute to giving accurate predictions. To predict BP status, conditional decision making is utilized, while the ML approach SVM is utilized for the diabetes prediction. SVM proved to be accurate in the diabetes prediction from diastolic BP measurements and glucose by achieving 75% accuracy [24].

By using ML, Nguyen et al. (2024) proposed a wearable device that can detect HR, falls, early CVD conditions, and initiate alerts in case of any abnormality reported. HR and ECG signals are collected through sensors. The collected data is then preprocessed to classify, filter noise, and remove other artifacts from the ECG signals. The data is collected by integrating the LSTM model, which was trained for 100 epochs. The LSTM is responsible for predicting ECG signals, and LSTM-Autoencoder is used to detect early abnormalities in the ECG signals with 94% accuracy [9].

Gangadhar et al. (2025) proposed a fall detection system by using ensemble ML techniques for healthcare of senior citizens. The authors used wearable sensors to detect falls. It reduces damage by triggering alarms when a human body hits a hard surface. When the ensemble of RF and SVM is tested on the KFall dataset, it transcends the modern fall detection techniques by achieving accuracies of 95% for non fall, 96% for pre fall, and 98% for falls [2].

By using ML techniques, Rajpoot et al. (2025) proposed a CPS framework for heart stroke monitoring and prediction of stroke. The system consists of two layers, i.e., the cyber layer and the physical layer. The physical layer collects data through sensors and transmits data to edge devices like smartphones. After the collection of raw data from sensors, the Cyber Layer plays an important role in data preprocessing by eliminating noise and other artifacts. For making accurate and efficient predictions, feature selection and data balancing (SMOTE, oversampling, undersampling) are done to balance imbalanced classes in the dataset. After the preprocessing and data cleaning process, the model is then trained using multiple algorithms like LR, RF, and SVM; but the RF regression model achieves the best optimal results by identifying the heart stroke cases with an accuracy of 95.7%. As a statistical methodology Kruskal Wallis H Test is done for the data merge validation. In short, the physical layer collects data via sensors while the cyber layer is involved in data preprocessing, decision making, and generating alarms in case of any abnormality [14].

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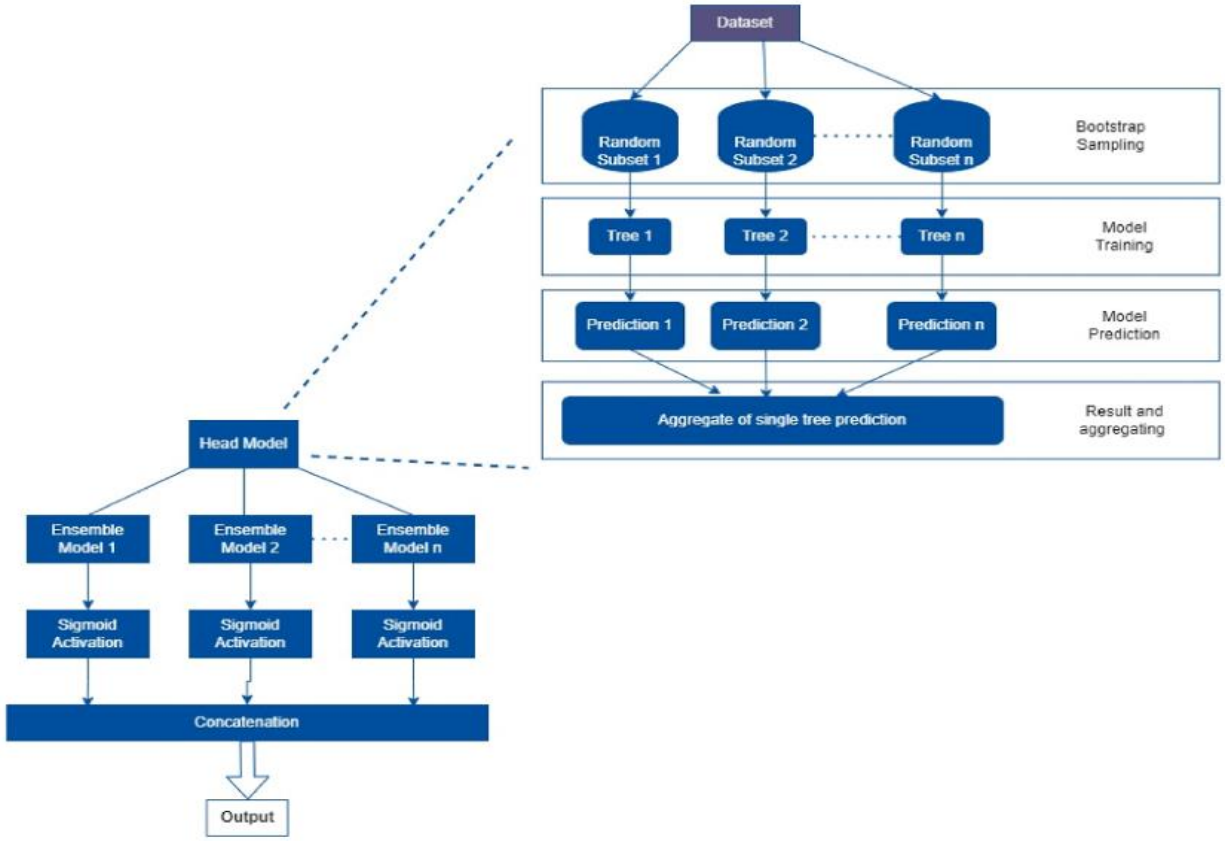


Figure 3. Class-based ensemble model [2]

3.3 Deep Learning Based Systems

Jain et al. (2022) presented a DL based fall detection system (FDS). It can detect falls within 0.5s in its initial phase. The system is trained on two standard datasets, i.e., KFall and SisFall. For developing FDS, FallNet is utilized, which is a deep neural classifier based on an ensemble of 1D CNN and LSTM. Stratified K Fold cross validation is utilized to train FallNet. The generalizability of the model is enhanced by the feature fusion of SisFall and KFall datasets. Moreover, Transitional Window (Tw) is utilized to increase the reaction time of the FDS, and the feature extraction methodology is validated with the laboratory verified results [15].

To detect falls in senior citizens, Anitha et al. (2022) proposed a system by utilizing the VEFED-DL (vision based elderly fall event detection using deep learning) model. The data is preprocessed to remove noise and other artifacts to enhance the features in the images. A normalization technique is applied to enhance the model generalizability. Based on MobileNet and GRU, spatial and temporal features are extracted, respectively. The data classification process is based on the SAE. GTOA method is utilized for parameter tuning and improving the fall detection rate. VEFED-DL is tested using the MCF and URFD datasets [13].

For accurate ES detection and automatic an EEG based framework is proposed by Torkey et al. (2025), where the system utilizes hybrid DL models including CNN, LSTM, and GRU for accurate diagnosis. To analyze and to enhance the interpretability of the models, an XAI technique (SHAP) is utilized, where SHAP utilized in the medical decision making. The epileptic seizure (ES) dataset contains imbalanced classes and is then further preprocessed by using the SMOTE technique to address the class imbalance issue.

The model is then trained and tested on an 80/20 ratio (20% data for the testing phase and 80% data for the training phase). The proposed model achieves accuracies without the SMOTE technique and with the SMOTE technique of 0.9787 and 0.9913, respectively [11].

3.4 Integration of Optimization Algorithms and Classifiers

To optimize the classification algorithms, including RF, SVM, KNN, LR, NB, DT, and MLP, Le et al. (2021) uses Grey Wolf Optimization (GWO) and Adaptive Particle Swarm Grey Wolf Optimization (APGWO). The classifier models are trained on the UP Fall detection dataset to achieve the best possible accuracy (99%) in fall detection. KNN is used in training; computational complexity is zero, and predicting outcomes from the new data is simple. Moreover, RF is an accurate and powerful technique. However, these are the best performing models. In short, the authors suggested that these two models, RF and KNN, will be used for future research because of their performance, canceling out biases, and not having any overfitting problems [3].

For smart home care, Vaiyapuri et al. (2021) proposed an IoT enabled Fall Detection model using Optimal Deep Convolutional Neural Network (IMEFDODCNN) by enabling smartphones and DL algorithms to detect falls. The data is first preprocessed to remove noise and other artifacts in the data. It also improves the features in the video or images. A model normalization technique is applied to enhance generalizability. SqueezeNet network module is presented by the authors, which is utilized for feature extraction. Salp Swarm Optimization (SSO) algorithm is utilized to optimally tune the hyperparameters of the SqueezeNet model. For the classification process, the SSOA-VAE (Salp Swarm Optimization Algorithm and Variational Auto Encoder) model is utilized to classify falls by labelling them as a fall or non fall event. In the end, the proposed model is validated on the two datasets: URFD (99.57%) and MCFD (99.76%) [18].

For disease prediction and arrhythmia classification, Kumar et al. (2023) used a Flamingo optimization DCNN classifier. DCNN network trains data and classifies diseases by using 3 layers i.e. convolutional layer which plays role in the features extraction related to arrhythmia, second pooling layer is responsible for down sampling method is utilized to reduce dimensionality and improves accuracy, and fully connected layer gives output whether the person affected with the disease or not. The ECG data is preprocessed by using a standard scalar transform method, where normalization and noise are removed from the data. MITBIH dataset is used here for the arrhythmia prediction. By this proposed method, 98.5% accuracy is achieved [19].

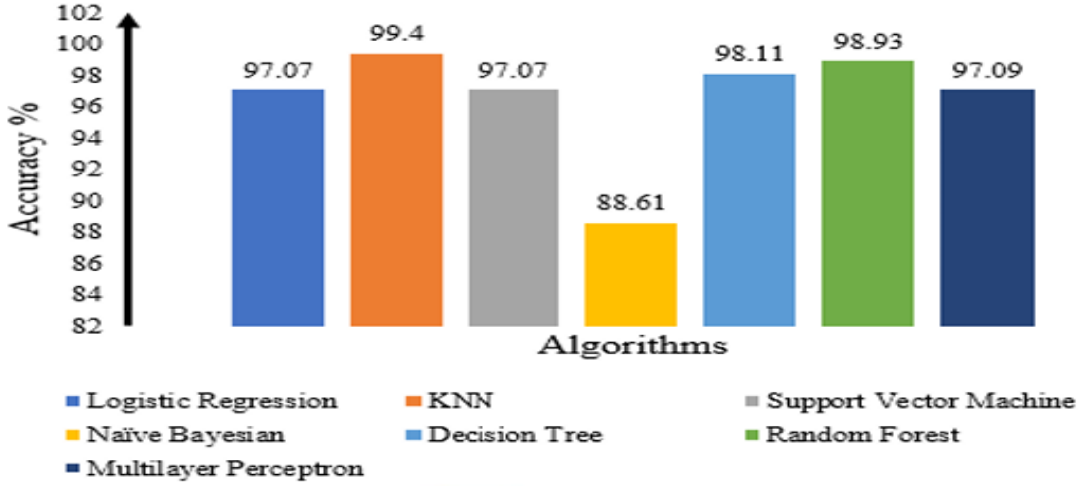


Figure 4. Classification accuracy of all algorithms [3]

3.5 IoT Based Frameworks

An IoT based system is proposed by Al-Kababji et al. (2021) to detect falls. Through a cloud connected gateway device, a sensing device transmits data to a mobile application. UniMiB-SHAR dataset is utilized for the study. Feature Extraction Algorithms are: CWT, which is utilized as a feature extraction method that would enhance the performance of the classifiers; SVM (Signal Vector Magnitude), a time domain feature that calculates acceleration generated by triaxial acceleration; SMA (Signal Magnitude Area), used to capture the change from the triaxial accelerometer; Triaxial accelerometer data range; and SE (Signal Energy). ML algorithms used here are: KNN (uses the whole dataset to classify events), ENN (has two ways of communication: checks ENN to test record and at the same time sees the test record of one of the nearest neighbors), BDT (model based classification that can break datasets into smaller subsets), and VM (takes a decision to detect ADLs and Fall events). The UniMiB-SHAR dataset used 5 folds (70/30) train/test ratio (KNN = 96.23%, ENN = 97.68%, BDT = 94.20, VM = 97.68%) and 10 folds (90/10) train/test ratio (KNN = 99.09%, ENN = 99.15%, BDT = 96.70, VM = 99.19%) [16].

Wang et al. (2022) presents an IoT based framework that consists of 5G and smart wearable technology with the integration of five sensors, including: an RFID reader, a pressure sensor, a passive infrared detector, a light sensor, and temperature sensors that can record indoor and physical conditions of the patients. The system consists of 3 layers: the perception layer, which can collect information from sensors; then the collected information is transmitted to the middle layer where information is processed, and then transmitted to the application layer, which involves the response based on the changes in patients' environment and conditions. To process and filter out the noise of the ECG signals, a finite pulse response digital filter is utilized. The data is collected through a clinical setup that consists of 64 dementia patients, out of which there are 35 males and 39 females, with ages ranging from 60 to 84 years old [28].

An IoT based system proposed by Cañón-Clavijo et al. (2023) involves the integration of a Polar H10 heart sensor and ML models for the classification of heart events. The system monitors ECG and processes heart data to generate alarms in case of any abnormality reported in the patients. The three classification algorithms, RF, CNN, and KNN, are utilized, where KNN performed well in the classification of supraventricular, ventricular, and fusion beat arrhythmias, but none of the algorithms

performed well on all arrhythmia classes. MIT BIH arrhythmia dataset is utilized to train models [26].

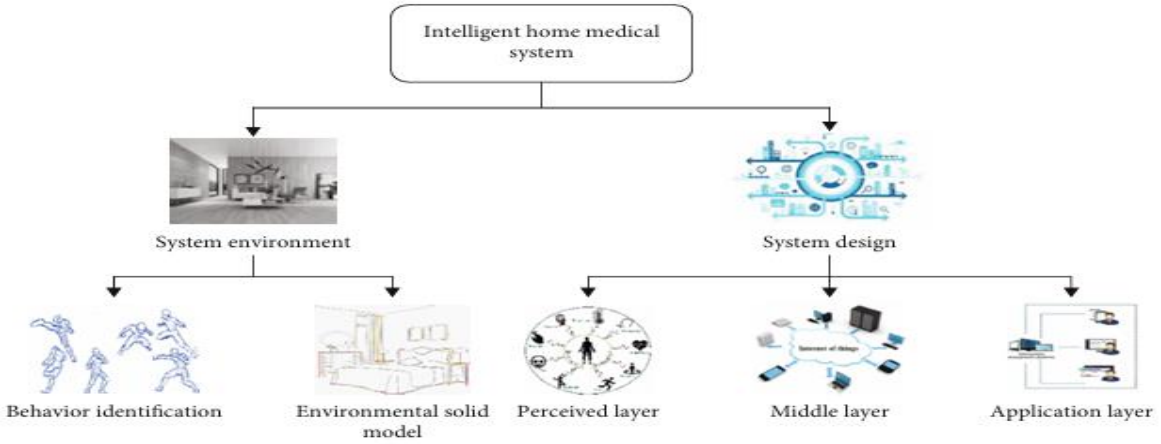


FIGURE 1: Model structure of intelligent home medical system.

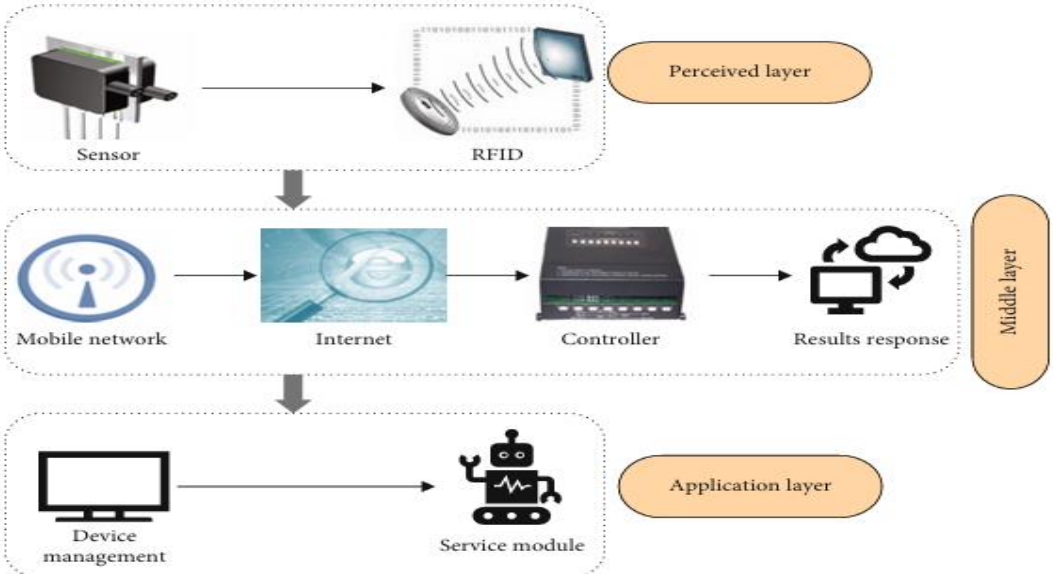


Figure 5. IoT based medical framework [28]

3.6 FFT and STFT

Choi et al. (2021) proposed a health monitoring system that can predict stroke related diseases in senior citizens in real time while walking. The raw EEG data is preprocessed by Fast Fourier Transform (FFT). Attributes are chosen by Correlation Feature Selection (CFS), and the algorithms used here are: RF, C4.5 DT, C5.0 DT, NB, MLP, LR, two class SVM, classification and regression tree (C&RT), and quick unbiased efficient statistical tree (QUEST) [22].

A smart walking cane is introduced by Adebiyi et al. (2022) to detect abnormal gait and tremor. To eliminate noise and other artifacts low pass band filter is utilized. Signal Magnitude Area (SMA) is utilized to make a difference between static and dynamic activities and for feature extraction. The features that include different ADLs like walking, pausing, and shaking. An energy feature, Short Time Fourier Transform (STFT), is utilized to check the velocity of these activities, whether it is slow or fast walking. Principal Component

Analysis (PCA) method is utilized to achieve dimensionality reduction. Likewise, Linear Discriminant Analysis (LDA) is a second order statistical and supervised classification approach used in the preprocessing step to classify different activities and patterns. For the experiment, the authors used one class SVM, achieving 98% accuracy [23].

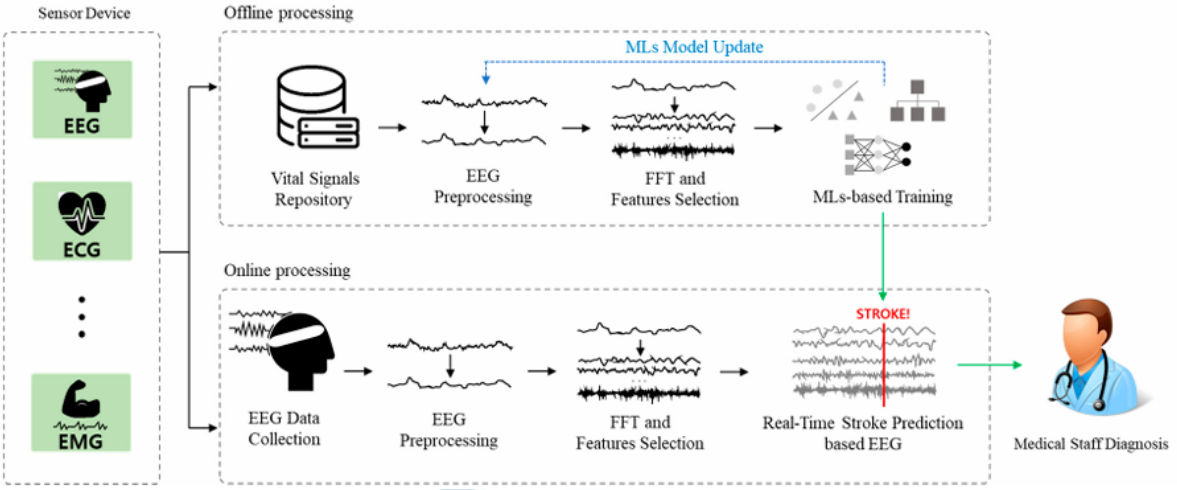


Figure 6. ML based stroke disease prediction [22]

3.7 Heart Stroke Prediction and Fall Detection

Tamilselvi et al. (2018) proposed a wearable device used to detect falls in paralyzed patients and senior citizens and heart stroke predictions. A heart rate sensor, humidity sensor, and temperature sensor are embedded in a wearable device. The output of the sensors is connected to the Raspberry Pi, and the sensor data is saved on the cloud. The unsupervised ML algorithm is used to compare the sensory data with the existing data. Heart stroke is predicted by using an ML algorithm. In case any abnormality is detected, an alert is generated through IoT communication technology [17].

4. RESULTS

The results chapter provides a comprehensive overview of the existing fall detection and prediction systems. Where the overview is provided by comparatively comparing the methodologies of the existing studies. This comparative analysis includes the algorithms, models, datasets, evaluation metrics, and the limitations of each existing study.

Table 6. Performance of systems reported in 2021

Reference	Model/ Algorithms/ Classifiers	Accuracy/Evaluation Metrics (Acc, Pre, Spe, Sen, F1)	Dataset	Limitations
Le et al. (2021) [3]	RF, SVM, KNN, LR, NB, DT, and MLP Optimization algorithms GWO and APGWO	RF = 98.93%, SVM = 97.07%, KNN = 99.4%, LR = 97.07%, NB = 88.61%, DT = 98.11%, and MLP = 97.09%. By applying Optimization algorithms: GWO: RF = 98.65%,	UPFall dataset	Feature selection parameter: MLP is not optimized, and the authors only included the indoor environment for their research.

		SVM = 97.07%, KNN = 99.3% (F1score = 82.32%), LR = 97.07%, NB = 91.37%, DT = 97.84%, and MLP = 97.1% (F1score = 96%). APGWO: RF = 98.71%, SVM = 97.07%, KNN = 99.25% (F1score = 84.79%), LR = 97.06%, NB = 93.29%, DT = 97.95%, and MLP = 97.09% (F1score = 96%).		
Vaiyapuri et al. (2021) [18]	IMEFD-ODCNN model, Optimization algorithms: SSOA-VAE	MCFD: accuracy 99.76%, URFD: accuracy 99.57%	MCFD and URFD datasets	Poor performance on low quality videos; class imbalance in URFD, where 74 frames for fall events, 240 frames for non fall events, and there is no real time deployment testing.
Farooq et al. (2021) [10]	ML approach named K-Means Clustering	No accuracy metrics used here	Self collected data of 3 patients	Extremely small dataset because only 3 patients were included
Choi et al. (2021) [22]	ML algorithms: RF, C4.5 DT, C5.0 DT, NB, MLP, LR, two-class SVM, C&RT (classification and regression tree), and QUEST (quick unbiased efficient statistical tree).	RF: exhibits 87.52% accuracy on 10 fold CV dataset, and on the 20 fold CV dataset exhibits accuracy of 88.12%, The SVM algorithm on the 5 fold CV dataset exhibits accuracy of 72.07%, C4.5 DT algorithm: exhibits accuracy of 85.6%, MLP (ANN): exhibits accuracy of 90.83% on the 10 fold CV dataset	No publicly available dataset used here	-
Tang et al. (2021) [25]	CNN	AUC- ROC 0.957, and a sensitivity of 80%	self collected dataset	No proper dataset used here; interference in the consistency of

				the signals (like each part of the body generates different signals), and most of the seizure types are not investigated here.
Al-Kababji et al. (2021) [16]	ENN, KNN, and BDT	5 folds (70/30) train/test ratio (KNN = 96.23%, ENN = 97.68%, BDT = 94.20, VM = 97.68%), 10 folds (90/10) train/test ratio (KNN = 99.09%, ENN = 99.15%, BDT = 96.70, VM = 99.19%)	UniMiB-SHAR dataset	Limited battery charge and discomfort in wearing WSDs

In 2021, authors presented systems to detect and monitor falls either by wearable and non wearable sensors. The authors used ML algorithms to train systems on publicly available datasets like UP Fall, MCFD, URFD [3, 18], while some of the researchers used their own collected datasets [25, 10], where the accuracies reported lie between 72.07% and 99%. These presented systems are not efficient enough to be adapted. These systems reported several limitations, such as class imbalance issues, patients getting uncomfortable due to WSDs, and poor performance on low quality videos [18, 16]. Moreover, all seizure types were not investigated [25] in the presented research during 2021.

Table 7. Performance of systems reported in 2022

Reference	Model/ Algorithms/ Classifiers	Accuracy/Evaluation Metrics (Acc, Pre, Spe, Sen, F1)	Dataset	Limitations
Jain et al. (2022) [15]	FallNet (ensemble of 1D CNN and LSTM)	FallNet exhibits accuracy of 97.52%	SisFall and KFall datasets.	Mimics falls; all the subjects are healthy and young but not senior citizens. SisFall and KFall are the emulated datasets of young and healthy subjects, not tested on pathological gait, and there is no deployment on microcontrollers and sensor networks.
Wang 2022 [28]	IoT framework with 5G, smart	Accuracy in Behavioral feature extraction:	self collected dataset of	Included fewer samples; a network

	wearable technology, Multi sensor indoor deployment, FIR digital filtering, clinical study of 64 dementia patients	74.59% - 98.33% and Correct behavior recognition: >98.5%	dementia patients	backhaul was only tested for temperature data; other signals like ECG signals were not verified for transmission accuracy.
Idrees et al. (2022) [20]	ESDNB, KCHE	ESDNB: accuracy from 99.95% up to 99.99%, for three-class classification, ESDNB provides accuracy from 99.53% up to 99.98%, for five classes classification, ESDNB provides an accuracy of 99.98%; KCHE: accuracy from 85.6 % up to 89.2%	Bonn University Dataset	KCHE has less compression power
Adebiyi et al. (2022) [23]	Isolation Forest, one class SVM	Isolation Forest exhibits accuracy of 0.96 One class SVM exhibits accuracy of 0.98	Self collected data set	Prone to type 2 error
Chatrati et al. (2022) [24]	ML algorithms	SVM exhibits accuracy of 75%, KNN exhibits accuracy of 74%, DT exhibits accuracy of 66.1%, LR exhibits accuracy of 74.5%, DA exhibits accuracy of 74.7%	Pima Indians Diabetes Database	Raw dataset used here requires processing before given to model, and manual data entry only.
Hassan et al. (2022) [27]	fuzzy logic algorithm	Body Temperature: 98.90%, Heart Rate Monitoring: 95.49%, Muscle Spasm: 83.0%, Fall Detection: 87.21%	No publicly available dataset used here	No publicly available dataset used here
Anitha et al. (2022) [13]	VEFED-DL model, GTOA (group teaching optimization algorithm), SAE model	URFD: accuracy of 99.98%, MCF: accuracy of 99.92%	URFD and MCFD	Small datasets: URFD, which consists of 314 frames, of which 74 are for fall events, 240 for no-fall events, and MCF contains 192

				videos, of which 96 are for fall events and 96 for regular events.

Likewise, in 2022, authors presented systems to detect and monitor falls by using ensemble machine learning techniques, ML, fuzzy logic, and optimization algorithms. The trained systems were trained on publicly available datasets like UP Fall, MCFD, URFD, SisFall, KFall, and Pima Indians Diabetes Database [13, 24, 15], while some of the researchers used their own collected datasets [23], where the accuracies reported lie between 74.59% and 99.98%. But these presented systems reported many flaws, which makes them unreliable to be adapted. Moreover, the limitations reported are the type 2 error; SiSFall and KFall are the emulated fall datasets, and URFD and MCFD are considered as the small datasets, which affects the efficiency and the reliability of the systems [15, 23, 13].

Table 8. Performance of systems reported in 2023

Reference	Model/ Algorithms/ Classifiers	Accuracy/Evaluation Metrics (Acc, Pre, Spe, Sen, F1)	Dataset	Limitations
Kumar et al. (2023) [19]	DCNN model, flamingo optimization	Accuracy: epoch value 100 using 80% of the training data is 97.612% (with epoch 20), 97.774% (with epoch 40), 97.808% (with epoch 60), 97.821% (with epoch 80), and 97.836% (with epoch 100)	MIT-BIH dataset	No clinical deployment
Cañón-Clavijo et al. (2023) [26]	KNN, RF, and CNN	RF (N = 93%, Q = 97%), KNN (V: 94%, F: 81%, S: 82%), CNN (N: 83%, S: 48%, V: 61%)	MIT-BIH-Arrhythmia dataset	CNN is not correctly detecting S and V type arrhythmias; RF does not perform well in comparison to CNN; KNN performs well on F class arrhythmias, and there is no single algorithm that performs well on all classes

Similarly, in 2023, authors presented arrhythmia detection systems where they used a DCNN model, flamingo optimization, KNN, RF, and CNN to train the model on the MIT-BIH dataset. However, when the system is trained on the dataset using KNN, accuracies scored for V are 94%, for F are 81%, for S are 82%, RF accuracies scored for N are 93%, for Q are 97%, and CNN accuracies scored for N are 83%, for S are 48%, V are 61% [19, 26]. But these presented systems reported some limitations that make them less efficient and not reliable. Moreover, there is no

clinical deployment [19], and none of the algorithms perform well on all classes [26], which makes the system less efficient in detecting arrhythmia conditions.

Table 9. Performance of systems reported in 2024

Reference	Model/ Algorithms/ Classifiers	Accuracy/Evaluation Metrics (Acc, Pre, Spe, Sen, F1)	Dataset	Limitations
Nguyen et al. (2024) [9]	LSTM model	0.94 precision, 0.98 recall, and 0.96 F1score.	No publicly available dataset used here.	The prediction of potential risks is 3 sec ahead from the current time, which is too short in case of serious health issues to predict abnormalities over a longer time.
Yedurkar et al. (2024) [21]	Radial Basis Function SVM (RBFSVM), CNN, and KNN, SSCSV	SVM exhibits accuracy 96.447% CNN exhibits accuracy 98.48%	TUH EEG: an epileptic EEG multichannel benchmark dataset	No examination of other seizure types
Basavaiah et al. (2024) [12]	SVM, LR, CNN	CNN achieves an accuracy of 95.26%, RF achieves an accuracy of 92.93%, and LR achieves an accuracy of 93.68%.	Data collected from hospitalized patients	Current models are not optimally trained and have no data security mechanism.

In 2024, authors presented fall detection systems by using ML models like LSTM [9]. Overall, >91% accuracies scored when trained on datasets like TUH EEG, which is an epileptic EEG multichannel benchmark dataset, and the data collection is done by getting data from hospitalized patients [21, 12]. But some limitations affect the efficiency and reliability of the systems. Moreover, the limitations are that the prediction of potential risks is 3 sec ahead of the current time, which is too short for serious health issues to predict abnormalities over a longer time, and models are not trained optimally [9, 12].

Table 10. Performance of systems reported in 2025

Reference	Model/ Algorithms/ Classifiers	Accuracy/Evaluation Metrics (Acc, Pre, Spe, Sen, F1)	Dataset	Limitations
Khan et al. (2025) [8]	SVM, KNN, RF	SVM exhibits accuracy of 97.26% KNN exhibits accuracy 72.69% RF exhibits accuracy 99.89%	CHB-MIT scalp EEG dataset	-

Gangadhar et al. (2025) [2]	Ensemble of RF and SVM	Non Fall (0.96), Pre Fall (0.94), Fall (0.98)	KFall dataset	Dataset includes young people only, but the target is senior citizens
Rajpoot et al. (2025) [14]	SVM and LR model	LR exhibits accuracy 92.3%, SVM exhibits accuracy 89.8%	No publicly available dataset used here	No DL models used here, like CNN & LSTM; latency concerns, and there is no edge/cloud optimization.
Torkey et al. (2025) [11]	Hybrid DL models, i.e., CNN, LSTM, GRU	Hybrid model with SMOTE exhibits accuracy 0.9913 Hybrid model without SMOTE exhibits accuracy 0.9787	Epileptic seizure recognition dataset	Absence of external evaluation on diverse datasets, limited generalizability, synthetic data bias, management of the sensitive medical data, high computational demands, and scalability and integration issues reported

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Lastly, in 2025, Hybrid DL models, which includes CNN, LSTM, GRU and ensemble ML techniques like; ensemble of RF and SVM are utilized to detect falls and seizures [2, 11] where the accuracies reported are >71% when trained on the datasets like; CHB-MIT scalp EEG dataset, KFall dataset, and Epileptic seizure recognition dataset [8, 2, 11]. But the system exhibits several limitations that affect the efficiency and accurate real world fall detection. So, there is limited generalizability, high computational demands, scalability and integration issues, absence of a diverse dataset, latency concerns, KFall includes data of young adults only instead of including young adults, and lack of DL model utilization [11, 14, 2].

5. CONCLUSION

In this review paper, the authors provide a comprehensive overview of existing fall detection and prediction systems. The most common cause of injuries and deaths of older people is falls. The number of accidental falls among elderly adults (over 65 years old) is about 28-35% annually. The number of such accidents among those older than 75 years equals approximately 40%. Accidental falls are highly important for young adults with some kind of neurological dysfunctions such as ES. Unfortunately, the previous literature provides little information on the matter; to a certain extent, the existing systems are not efficient and reliable. Fall predictions achieve high accuracies, but the time needed to predict a certain risk equals several seconds. But datasets like KFall have unbalanced class issues. Some video based approaches suffer from generalizability issues. Besides, the use of sensors leads to lower battery lifetime and discomfort for the patient. In order to improve the system performance, the authors recommend the use of intermediate sensors to reduce the second type of errors and real time detection problems.

REFERENCES

Analysis of Sensor Modalities and Computational Models. Applied Sciences. DOI: https://doi.org/10.3390/app16041929

[2] Gangadhar, Ch., et al. (2025) Wearable Sensor-Based Fall Detection for Elderly Care Using Ensemble Machine Learning Techniques. Measurement: Sensors. DOI: https://doi.org/10.1016/j.measen.2025.101870

[3] Le, T. M., et al. (2021) A Feature Selection Approach for Fall Detection Using Various Machine Learning Classifiers. IEEE Access, Vol. 9. DOI: https://doi.org/10.1109/ACCESS.2021.3105581

[4] Praveen, S. P., et al. (2025) AI-Powered Diagnosis: Revolutionizing Healthcare with Neural Networks. Journal of Theoretical and Applied Information Technology, Vol. 103, No. 3. Available at: https://www.jatit.org/volumes/Vol103No3/16Vol103No3.pdf

[5] Anwer, M. S., et al. (2024) Opportunities and Challenges of Artificial Intelligence-Powered Technology in Healthcare. Medical Research Archives, 12(3). DOI: https://doi.org/10.18103/mra.v12i3.5141

[6] Nazil, A. R., et al. (2025) AI-Powered Visualization is Transforming Modern Healthcare. International Journal for Multidisciplinary Research, Vol. 7, Issue 4. DOI: https://doi.org/10.36948/IJFMR.2025.V07I04.53087

[7] Khalifa, M., et al. (2024) AI in Diagnostic Imaging: Revolutionising Accuracy and Efficiency. Computer Methods and Programs in Biomedicine Update, Vol. 5. DOI: https://doi.org/10.1016/j.cmpbup.2024.100146

[8] Khan, F. A., et al. (2024) Explainable AI for Epileptic Seizure Detection in Internet of Medical Things. Digital Communications

[1] Ishaq, M., et al. (2025) A Systematic Review of Fall Detection and Prediction Technologies for Older Adults: An and Networks. DOI: https://doi.org/10.1016/j.dcan.2024.08.013

[9] Nguyen, V.-T., et al. (2024) Development of a Wearable Device for Heart Rate Monitoring and Fall Detection Using Machine Learning to Analyze and Detect Early Anomaly of Cardiovascular Conditions. Vol. 22, No. 6A. DOI: https://doi.org/10.31130/ud-jst.2024.158ICT

[10] Farooq, A., et al. (2021) A Wearable Wireless Sensor System Using Machine Learning Classification to Detect Arrhythmia. IEEE Sensors Journal, Vol. 21, No. 9. DOI: https://doi.org/10.1109/JSEN.2021.3062395

[11] Torkey, H., et al. (2025) Seizure Detection in Medical IoT: Hybrid CNN-LSTM-GRU Model with Data Balancing and XAI Integration. Algorithms, 18, 77. DOI: https://doi.org/10.3390/a18020077

[12] Basavaiah, J., et al. (2024) An Efficient Approach of Epilepsy Seizure Alert System Using IoT and Machine Learning. Journal of Reliable Intelligent Environments, 10, 449-461. DOI: https://doi.org/10.1007/s40860-024-00228-w

[13] Anitha, G., et al. (2022) Vision Based Real Time Monitoring System for Elderly Fall Event Detection Using Deep Learning. Computer Systems Science and Engineering. DOI: https://doi.org/10.32604/csse.2022.020361

[14] Rajpoot, N. K., et al. (2025) An Intelligent Framework for Real-Time Heart Stroke Monitoring and Early Detection Using Machine Learning. DOI: https://doi.org/10.7759/s44389-025-04004-6

[15] Jain, R., et al. (2022) A Novel Feature Extraction Method for Preimpact Fall Detection System Using Deep Learning and Wearable Sensors. IEEE Sensors Journal, Vol. 22, No. 23. DOI: https://doi.org/10.1109/JSEN.2022.3213814

[16] Al-Kababji, A., et al. (2021) An IoT-Based Framework for Remote Fall Monitoring. Biomedical Signal Processing and Control. DOI: https://doi.org/10.1016/j.bspc.2021.102532

[17] Tamilselvi, A., et al. (2018) A Wearable Device for Fall Detection and Heart Stroke Prediction Using IoT and Machine Learning. Available at: https://www.rrjp.in/admin/papers/Tamilselvi%202018.pdf

[18] Vaiyapuri, T., et al. (2021) Internet of Things and Deep Learning Enabled Elderly Fall Detection Model for Smart Homecare. IEEE Access, Vol. 9. DOI: https://doi.org/10.1109/ACCESS.2021.3094243

[19] Kumar, A., et al. (2023) Flamingo-Optimization-Based Deep Convolutional Neural Network for IoT-Based Arrhythmia Classification. Sensors, 23, 4353. DOI: https://doi.org/10.3390/s23094353

[20] Idrees, A. K., et al. (2022) An Edge-Fog Computing-Enabled Lossless EEG Data Compression with Epileptic Seizure Detection in IoMT Networks. IEEE Internet of Things Journal, Vol. 9, No. 15. DOI: https://doi.org/10.1109/JIOT.2022.3143704

[27] Hassan, S., et al. (2022) IoT Based Monitoring System for Epileptic Patients. Heliyon. DOI: https://doi.org/10.1016/j.heliyon.2022.e09618

[28] Wang, Q., et al. (2022) Computer Internet of Things-Based Intelligent Medical System to Be Applied in Home Care of Senile Dementia Patients. Journal of Healthcare Engineering, Vol. 2022, Article ID 1374835.

[21] Yedurkar, D. P., et al. (2024) An IoT-Based Novel Hybrid Seizure Detection Approach for Epileptic Monitoring. IEEE Transactions on Industrial Informatics, Vol. 20, No. 2. DOI: https://doi.org/10.1109/TII.2023.3274913

[22] Choi, Y.-A., et al. (2021) Machine-Learning-Based Elderly Stroke Monitoring System Using Electroencephalography Vital Signals. Applied Sciences, 11, 1761. DOI: https://doi.org/10.3390/app11041761

[23] Adebiyi, M. O., et al. (2022) Abnormal Gait and Tremor Detection in the Elderly Ambulatory Behavior Using an IoT Smart Cane Device. BioMedInformatics, 2, 528-543. DOI: https://doi.org/10.3390/biomedinformatics2040033

[24] Chatrati, S. P., et al. (2022) Smart Home Health Monitoring System for Predicting Type 2 Diabetes and Hypertension. Journal of King Saud University - Computer and Information Sciences. DOI: https://doi.org/10.1016/j.jksuci.2020.01.010

[25] Tang, J., et al. (2021) Seizure Detection Using Wearable Sensors and Machine Learning: Setting a Benchmark. Epilepsia, 62, 1807-1819. DOI: https://doi.org/10.1111/epi.16967

[26] Cañón-Clavijo, R. E., et al. (2023) IoT Based System for Heart Monitoring and Arrhythmia Detection Using Machine Learning. Journal of Healthcare Engineering. DOI: https://doi.org/10.1155/2023/6401673
DOI: https://doi.org/10.1155/2022/1374835