Jurnal Teknik Informatika (JUTIF)
P-ISSN: 2723-3863
E-ISSN: 2723-3871

Vol. 6, No. 6, December 2025, Page. 5956-5975
https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2025.6.6.5440

A Hybrid Deep Learning Architecture for Cost-Effective, Real-Time IV Infusion Anomaly Detection using IoT Sensors

Muhammad Brian Nafis*[1], Cinantya Paramita[2], Sasha-Gay Wright[3]

[1]Faculty of Computer Science, Universitas Dian Nuswantoro, Semarang, Indonesia
[2]Dinus Research Group for AI in Medical Science (DREAMS), Universitas Dian Nuswantoro, Semarang, Indonesia
[3]Biomedical Engineering, Faculty of Engineering, University of the West Indies Mona, Jamaica

Email: [2]111202214513@mhs.dinus.ac.id

Received : Nov 12, 2025; Revised : Nov 30, 2025; Accepted : Dec 13, 2025; Published : Dec 31, 2025

Abstract

Intravenous (IV) infusion therapy is a critical medical procedure, yet manual monitoring increases the risk of complications such as air embolism and irregular infusion flow, particularly in resource-constrained environments. Although several automated infusion monitoring systems have been proposed, their high implementation cost limits practical adoption. This research develops a low-cost IoT-based infusion monitoring system capable of real-time anomaly detection using a multi-architecture machine learning approach. The proposed prototype integrates an ESP32 microcontroller with load cell (HX711) and optical (LM393) sensors to acquire time-series infusion data. Ten models from classical machine learning, deep learning, hybrid, and ensemble categories were evaluated using a dataset of 10,420 records under a unified experimental setup. The results show that XGBoost had a perfect recall (1.0000) and a strong PRAUC, while the LSTM Autoencoder had the highest F1-Score (0.9343) and precision (0.8934). The best overall performance came from hybrid and ensemble methods, with CNN–LSTM having an F1-Score of 0.89, a recall of 0.99, and a precision of 0.80. This means they would be great for clinics where being sensitive is very important. The research shows that using a low-cost IoT infrastructure with carefully chosen deep learning or ensemble models can help find problems in real time. A web dashboard explains how the technology operates and its capabilities. This study examines a cost-effective and easily scalable method to enhance infusion safety in hospitals with limited financial resources.

Keywords : *Anomaly Detection, Deep Learning, Ensemble Learning, Internet of Things, Infusion Monitoring, Real-Time Systems.*

1. INTRODUCTION

Intravenous (IV) infusion therapy is a prevalent therapeutic practice in hospitals, with more than 80% of inpatients necessitating continuous fluid administration during their hospitalization [1], [2], [3]. The infusion process is crucial for maintaining patients physiological stability as it regulates the precise administration of fluids, drugs, and nutrients. However, manual monitoring by medical staff often leads to negligence, such as when an IV bottle runs out while the nurse is attending to another patient. These conditions can cause delayed responses, blood backflow, or air emboli, especially when there is a lot of work to do or not enough medical staff [4], [5], [6]. Data from the World Health Organization (WHO) show that intravenous medication mistakes are one of the most common causes of patient injury in hospitals. There are five times more chances of them happening than mistakes made when giving medicine in other ways [7]. There are a lot of Internet of Things (IoT)-enabled automated infusion devices with high accuracy and closed-loop control systems. However, they can't be used because they need parts that are certified for medical use and microcontrollers that are certified for industrial use, which makes them more expensive to make. The goal of this project is to create a cheap IoT-based

Vol. 6, No. 6, December 2025, Page. 5956-5975
https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2025.6.6.5440

prototype for infusion monitoring that ensures clinical detection accuracy and reliability. This will give healthcare organizations with limited resources an affordable option [8], [9].

The Internet of Things (IoT) has grown so quickly that it is now possible to make real-time medical monitoring systems that can collect, send, and analyze data from sensors that are all connected to each other [10]. The quick growth of the Internet of Things (IoT) has made it possible to make real-time medical monitoring systems that can gather, send, and analyze data from sensors that are connected to each other. The rapid development of IoT has facilitated the creation of real-time medical monitoring systems that can collect, transmit, and analyze data from interconnected sensors. Modern infusion systems use sensors such as load cells for weight measurement and LM393 optical sensors to continuously detect the drip rate of intravenous fluids [10], [11]. The data obtained from both sensors is processed by the ESP32 microcontroller and stored in a MySQL database for further analysis. The measurement results can be displayed on a 0.91" OLED screen and visualized on a real-time web monitoring system that shows warning notifications if there are any anomalies in the infusion rate [12], [13].

Various studies have proposed artificial intelligence approaches to improve the accuracy of medical anomaly detection. The CNN-LSTM hybrid model with federated learning is reported to achieve 94% accuracy with a low detection error rate in real-time anomaly detection scenarios [14]. Other research shows that sequential models like LSTM are better at understanding long-term patterns in medical data [15]. Furthermore, unsupervised learning methods such as Isolation Forest and Local Outlier Factor have been employed to detect anomalies in propofol infusion patterns, producing better results compared to threshold-based methods [16]. Another study developed a system for monitoring drip rates utilizing optical sensing and deep learning. On the other hand, a study that used this model used infrared sensors and logistic regression to keep an eye on infusions [17]. Most of these studies, on the other hand, only use one type of model architecture, either classical machine learning or deep learning [18], [19], [20], [21], [22].

Even with these improvements, there are still big gaps in the research that is already out there. Most prior studies evaluate only a single architecture either classical machine learning or deep learning without performing cross-architecture comparisons on real IoT infusion data [23], [24]. Many systems also depend on costly medical-grade hardware, making them unsuitable for deployment in low-resource hospitals. Furthermore, the majority of prior works rely on synthetic or limited datasets, with no unified benchmarking across heterogeneous models under the same preprocessing pipeline. These limitations leave unanswered questions regarding the optimal model family, the reliability of low-cost sensor integration, and the feasibility of a clinically scalable IoT-AI infusion monitoring system. This research fills these gaps by creating a cost-effective IoT prototype, building a real time-series dataset, and thoroughly testing ten models across classical, deep, hybrid, and ensemble architectures to find the best way to find anomalies in real time [25].

This study fixes the problem by looking at 10 models from different architectures, such as classical machine learning, deep learning, hybrid models, and ensemble models [26]. XGBoost, CatBoost, Random Forest, and Decision Tree were used as stable baseline models for tabular data in the classical machine learning category [27]. In the deep learning category, LSTM Classifier, 1D CNN, and LSTM Autoencoder were applied to capture temporal patterns from sequential infusion signals. For the hybrid approach, CNN-LSTM and Advanced CNN-LSTM were used to combine spatial and temporal representation capabilities. Finally, the Weighted Ensemble method is used to adaptively integrate the outputs of the best models, resulting in more stable and anomaly-sensitive predictions [28].

A total of 10,420 time-stamped records were collected from the ESP32-based infusion system prototype during a two-hour simulation. The evaluation results show that the XGBoost model had perfect PR-AUC and Recall scores (1.0000), while the LSTM Autoencoder had the best F1-Score

Vol. 6, No. 6, December 2025, Page. 5956-5975
https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2025.6.6.5440

(0.9343) and Precision (0.8934). These results indicate that the combination of sequential models and ensemble techniques is capable of improving the system's sensitivity to early detection of infusion anomalies.

The developed system has two application scenarios: (1) as an IoT-based prototype for independent local anomaly detection, and (2) as a real-time monitoring web platform for visualization and early warning. This approach not only supports the automation of clinical monitoring but also assists medical personnel in detecting potential depletion of intravenous fluids or irregularities in the drip rate. From a technical standpoint, this study aids in the benchmarking of ensemble architectures and deep sequential models according to stability, accuracy, and inference efficiency. From a practical perspective, this research illustrates the feasibility of creating a cost-efficient, adaptable, and integrable smart infusion monitoring system within the digital hospital environment.

2. METHOD

This research implements an integrated IoT system with machine learning for real-time detection of medical infusion anomalies, following a similar approach to previous smart healthcare studies [3], [10], [15]. The methodology consists of two main components: an IoT system for data collection and a machine learning system for classifying infusion conditions based on the temporal patterns of sensor data. The research stages were designed with reference to the standard CRISP-DM (*Cross-Industry Standard Process for Data Mining*) framework, which includes data preprocessing, modeling, and evaluation. This framework ensures end-to-end integration from physical devices to artificial intelligence-based analysis, creating a system that is efficient, adaptable, and ready for future clinical implementation development.

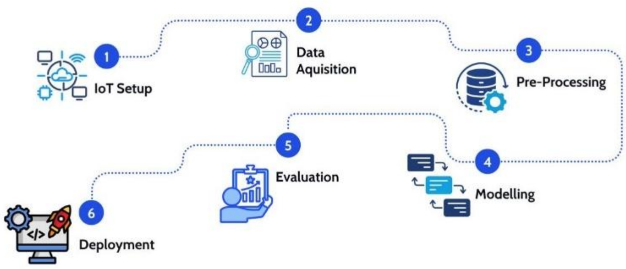


Fig. 1. End-to-End Research Workflow for IoT-Based Anomaly Detection System.

2.1. IoT Setup

The Internet of Things (IoT) system architecture developed in this study is designed to monitor infusion conditions in real-time and transmit sensor data to a server for further analysis using machine learning algorithms.

Fig. 2. IoT Hardware Configuration: (a) Front View of the optocoupler LM393. (b) Side View Showing Sensor Mounting. (c) System Wiring Diagram.

Jurnal Teknik Informatika (JUTIF)
P-ISSN: 2723-3863
E-ISSN: 2723-3871
Vol. 6, No. 6, December 2025, Page. 5956-5975
https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2025.6.6.5440

The system consists of one main end node based on ESP32 WROOM-32, which serves as the data processing and communication center between sensors. This node is connected to a Load Cell amplified by an HX711 module to measure the weight of the infusion fluid, as well as an LM393 infrared optical sensor to detect fluid drops in the infusion tubing. Information is displayed locally via a 0.91-inch OLED display (128×32 pixels), which automatically cycles between modes to show infusion status and system connection. This node design aligns with practices used in previous research [11], which implemented a combination of weight and optical sensors to precisely detect infusion flow dynamics.

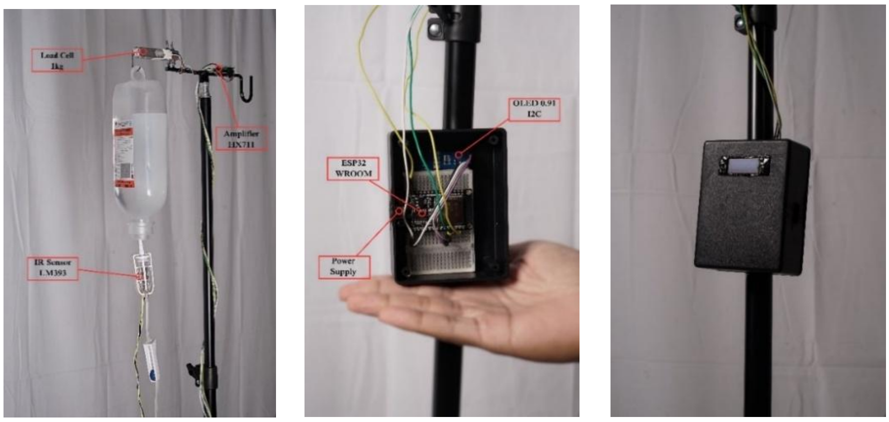


Fig. 3. Prototype Assembly Details: (a) Complete IoT System on Infusion Pole. (b) Internal View of the Main Enclosure. (c) Front View of the Monitoring Unit.

The hardware prototype is assembled in a modular casing that integrates with the infusion pole. The LM393 sensor is mounted vertically to detect drops in the infusion tubing, while the load cell and HX711 module are positioned under the infusion bottle to measure weight changes. The ESP32's main processing unit and the OLED display are located on the front for user accessibility. The design illustrated in Fig. 3 allows for the simultaneous acquisition of drip rate and fluid weight data in a compact and cost-effective package, aligning with previous end-node implementations in medical IoT systems [10], [11].

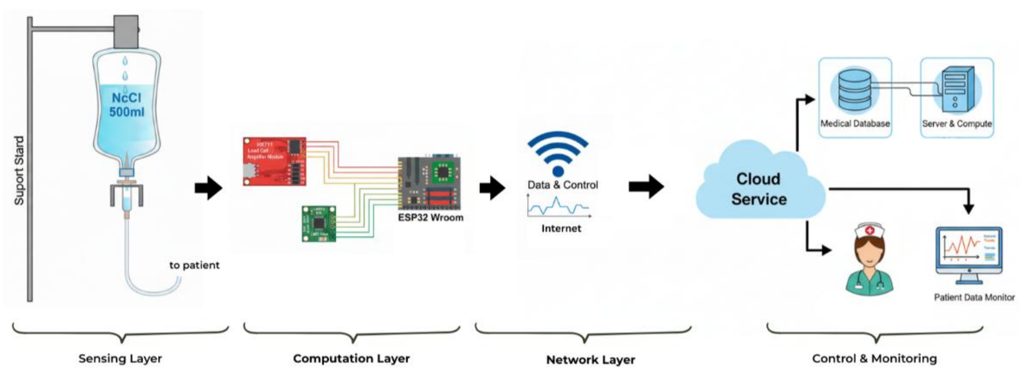


Fig. 4. Four-Layer IoT System Architecture.

The device is configured using the Arduino IDE with the WiFi.h and HTTPClient.h libraries for wireless communication over a Wi-Fi network. Data is sent using the HTTP POST protocol each time the LM393 sensor detects liquid droplets, so each entry represents a single actual physical event. The OLED display cycles thru three modes (Main Status, Droplet Statistics, and Status & Alert), using a non-blocking system to avoid interrupting the main sensor readings. This software architecture is built

Vol. 6, No. 6, December 2025, Page. 5956-5975
https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2025.6.6.5440

upon four system layers: (1) Sensing Layer (HX711 and LM393), (2) Computation Layer (processing on the ESP32), (3) Network Layer (transmission via Wi-Fi), and (4) Control & Monitoring Layer (data storage and visualization). This four-layer structure is widely applied in medical IoT research to ensure system modularity and reliability [3], [10], [11], [14].

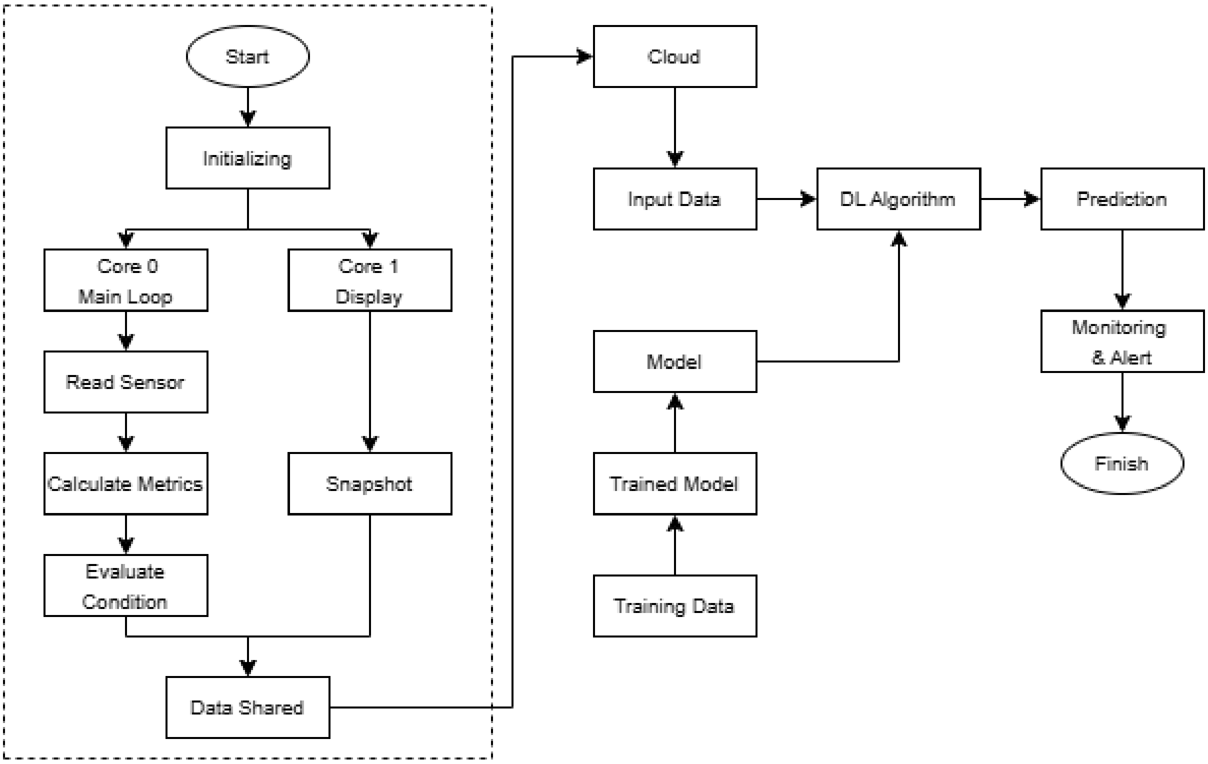


Fig. 5. Integrated Two-Stage Workflow of the AIoT System.

The overall system workflow consists of two main, integrated stages: data acquisition thru IoT devices and anomaly analysis based on machine learning. The HX711 and LM393 sensors are connected to the ESP32 module, which converts the measurement results into digital data before sending it to the server via Wi-Fi. The data stored on the server is then processed by the CNN-LSTM model to detect anomaly patterns in the infusion rate and weight. This system operates continuously, where each new data point collected automatically updates the central dataset to retrain the artificial intelligence model. Comprehensive integration between physical devices, cloud infrastructure, and artificial intelligence pipelines enables the system to operate end-to-end, efficiently, and adaptively to variations in medical conditions. A similar approach to building an AIoT-based pipeline for medical monitoring was also applied in previous research [14], which combined physical sensors and machine learning models to detect abnormal conditions in real-time.

2.2. Dataset & Preprocessing

The data processing flow in this study follows an integrated path that connects the IoT system with the machine learning pipeline, as shown in Figure 6. This pipeline consists of key stages ranging from acquiring raw data from IoT systems, cleaning the data, feature engineering, handling class imbalance, to splitting the dataset for model training and testing. This kind of integrated pipeline approach is commonly used in IoT-based time-series anomaly detection studies to maintain continuity between stages and avoid loss of temporal context [16], [17], [32].

Vol. 6, No. 6, December 2025, Page. 5956-5975
https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2025.6.6.5440

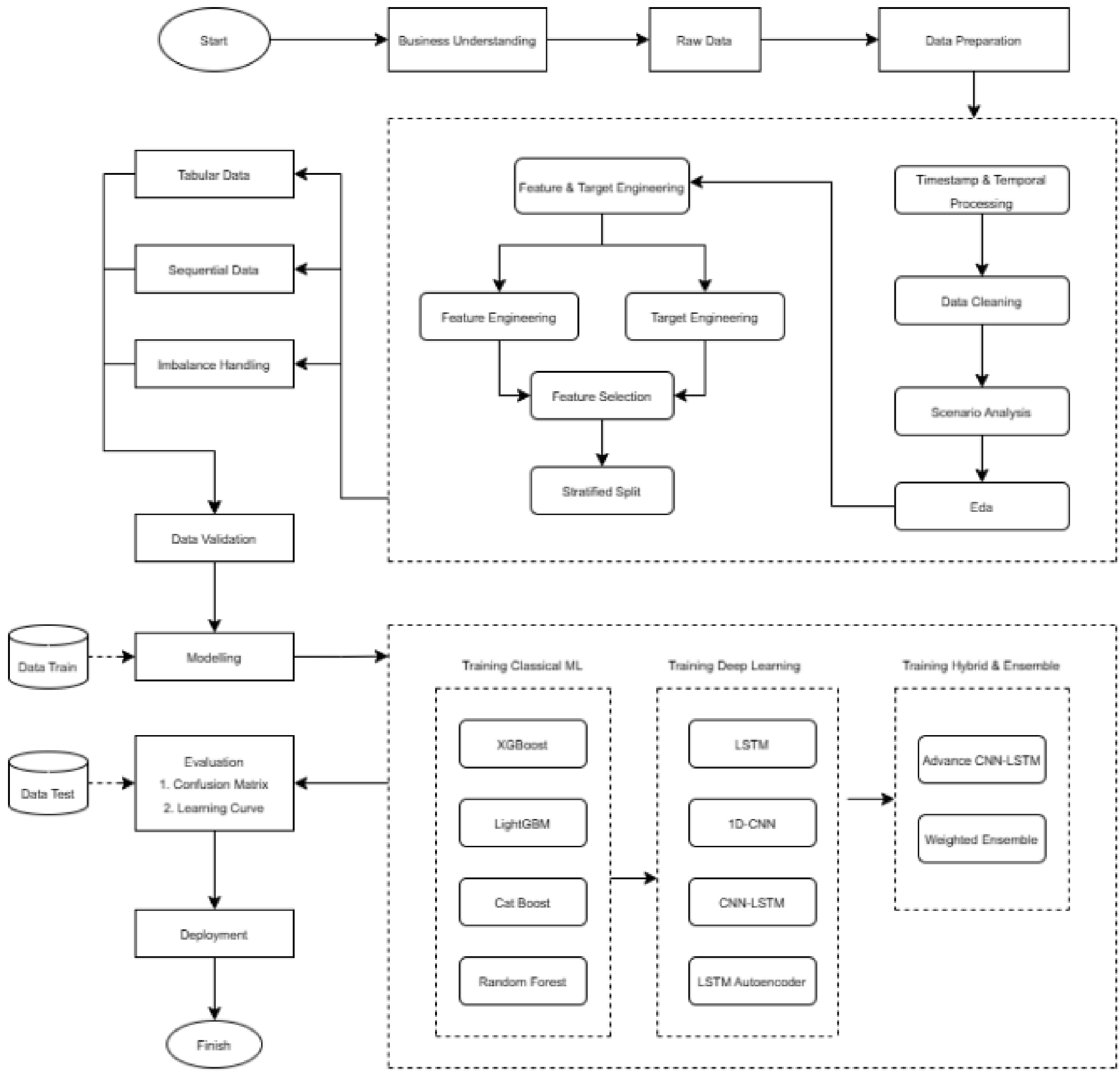


Fig. 6. End-to-End Data Processing and Model Deployment Pipeline.

The dataset used was obtained from the acquisition results of an ESP32 WROOM-32-based IoT system, which records infusion activity in real-time thru two main sensors: HX711 (Load Cell) for weight measurement and LM393 for drop detection. Each sensor reading is automatically sent to the MySQL server via the HTTP POST protocol, then exported to CSV format (infus_data.csv) for further analysis. The entire process was conducted in a controlled experimental environment (non-clinical simulated environment) to ensure data safety and replication, as is common practice in similar studies [10], [11].

From this acquisition process, 10,420 samples were generated with 12 raw attributes including weight, drip rate, cumulative number of drops, and time metadata. After timestamp alignment and feature engineering, the number of features increased to 93 derived features such as *rolling mean, rate of change, drip acceleration,* and *volatility metrics*, specifically designed to capture short-term and long-term dynamics in the infusion flow; of these, 18 final features were selected using a Random Forest-based feature importance method and correlation analysis to eliminate redundancy. Two additional columns, timestamp and scenario_id, were excluded from training because they were only used for identification and plotting purposes. Feature selection practices like this help maintain clinical relevance while suppressing uninformative feature dimensions [36], [37].

Vol. 6, No. 6, December 2025, Page. 5956-5975
https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2025.6.6.5440

The dataset is organized according to anomaly scenarios S1–S5 (Bubble, Blocked, Clamp, Fast Flow, Clamp Setting) so that each abnormal condition has a context that can be modeled specifically. This scenario division is used to enrich contextual labels so that the model can recognize different transition patterns and types of anomalies. an approach that has been proven to improve detection performance in pattern recognition-based studies for medical monitoring [37], [38].

The data preprocessing stage centered on handling the severe class imbalance, where the raw dataset initially exhibited a minor anomaly proportion of only 1.8%. To maintain the model's required sensitivity for detecting clinically critical, albeit rare, medical events, a scenario-aware threshold adjustment method was implemented, utilizing established clinical thresholds and domain expertise to redefine anomaly boundaries based on specific scenarios, thereby augmenting the proportion of anomaly events in the training dataset to 42.4%. This threshold-based approach was preferred as it strategically preserves the intrinsic temporal characteristics of the time-series data while significantly reducing the risk of overfitting often introduced by synthetic oversampling techniques [34], [35]. Furthermore, to robustly address the residual imbalance, class weight balancing was incorporated during the learning phase, a standard and effective practice in medical and time-series anomaly detection domains, which strengthens the penalty associated with misclassification errors in the minority class.

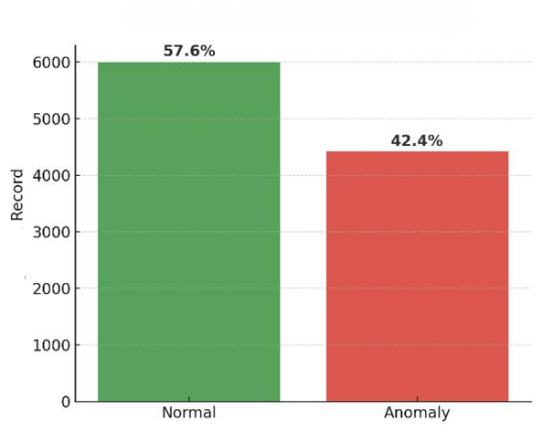


Fig. 7. Dataset Class Distribution.

For the needs of the deep learning model, the data is transformed into a sequential format via a window-based sampling approach with a window size of 50 timesteps and a stride of 5, resulting in a sequential representation (50, 6) as input for the LSTM/CNN-LSTM model. This windowing technique was chosen to allow the model to capture crucial long-term temporal patterns in real-time anomaly detection [33]. The dataset was then split using a temporal-aware stratified split (70% train, 15% val, 15% test) to maintain the temporal order and the proportion of anomalies in each subset, a strategy widely recommended for validation on health time-series datasets [39].

This temporal stratification approach ensures model generalization across time dynamics and reduces the risk of data leakage. The final dataset is organized in two formats: (a) tabular (30 features) for classical machine learning approaches, and (b) sequential (windowed) for deep learning models [28]. All preprocessing results are saved in.pkl and .csv formats to ensure experiment replication and consistency across model training phases.

This study employs a structured and fully transparent methodological pipeline covering data collection, preprocessing, feature engineering, relabeling, model training, and evaluation [16], [17]. The collected dataset consists of 10,420 time-stamped infusion records captured at ~1.2 Hz in a single continuous session using LM393 optical drip sensors and a load cell module [3], [10], [11]. From the raw measurements, 12 primary features were extracted (e.g., drop_rate, weight, delta_weight), and 18

Vol. 6, No. 6, December 2025, Page. 5956-5975
https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2025.6.6.5440

additional engineered features were generated, resulting in 30 tabular variables used for classical and ensemble models [33], [36]. For deep sequential architectures, six temporal features were transformed into sliding windows of 50 timesteps (50×6) [15], [20]. Because the original anomaly rate (1.8%) was derived solely from the firmware's narrow definition of "drip halt," a clinically grounded rule-based relabeling procedure was applied incorporating drip-rate safety thresholds, weight-stagnation patterns, and volatility indicators. This produced a natural anomaly proportion of 42.4% without oversampling, augmentation, or label manipulation, supported by window-level temporal dynamics. After relabeling, data were temporally split into training/validation/testing sets (70/15/15) prior to scaling to avoid leakage [39].

Table 1. Hyperparameter Models

Model	Key Hyperparameter	Training Configuration
Random Forest	n_estimators = 200	Random state = 42
	criterion = 'gini'	n_jobs = -1 (parallel)
	max_depth = None	
	min_samples_split = 2	
	min_samples_leaf = 1	
	class_weight = 'balanced_subsample'	
XGBoost	n_estimators = 200	tree_method = 'gpu_hist'
	scale_pos_weight = 1.36	random_state = 42
	learning_rate = 0.3 (default)	use_label_encoder = False
	max_depth = 6 (default)	
	subsample = 1.0 (default)	
	colsample_bytree = 1.0 (default)	
	eval_metric = 'logloss'	
LightGBM	n_estimators = 200	device = 'gpu'
	learning_rate = 0.1 (default)	random_state = 42
	num_leaves = 31 (default)	verbose = -1
	max_depth = -1 (default)	
	scale_pos_weight = 1.36	
	boosting_type = 'gbdt'	
CatBoost	iterations = 500	task_type = 'GPU'
	depth = 8	random_state = 42
	learning_rate = 0.03 (default)	verbose = 0
	loss_function = 'Logloss'	
	scale_pos_weight = 1.36	
	l2_leaf_reg = 3 (default)	
LSTM	units = 64	optimizer = Adam(lr=0.001)
	dropout = 0.3	epochs = 100
	recurrent_dropout = 0.2	batch_size = 32
	dense_units = 32 → 1	early_stopping (patience=15)
	activation = 'sigmoid'	
1D-CNN	filters = [32, 64]	optimizer = Adam(lr=0.001)
	kernel_size = 3	epochs = 100
	pool_size = 2	batch_size = 32
	dense_units = 64 → 1	early_stopping (patience=15)
	dropout = 0.5	

Vol. 6, No. 6, December 2025, Page. 5956-5975
https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2025.6.6.5440

CNN-LSTM	Conv1D filters = 32 → 64 LSTM units = 64 kernel_size = 3 pool_size = 2 dense_units = 32 → 1 dropout = 0.3	optimizer = Adam(lr=0.001) epochs = 100 batch_size = 32 early_stopping (patience=15)
LSTM Autoencoder	input_dim = 30 encoding_dim = 16 hidden_dim = 32 activation = 'relu' reconstruction_activation = 'sigmoid'	optimizer = Adam(lr=0.001) epochs = 150 batch_size = 32 loss = 'mse' early_stopping (patience=20)
Advanced CNN-LSTM	Conv1D layers: 32→64 filters Stacked LSTM: 64→32 units kernel_size = 3 dropout = 0.3 dense_dropout = 0.5	optimizer = Adam(lr=0.001) epochs = 100 batch_size = 32 early_stopping (patience=15)
Advanced CNN-LSTM	Conv1D layers: 32→64 filters Stacked LSTM: 64→32 units kernel_size = 3 dropout = 0.3 dense_dropout = 0.5	optimizer = Adam(lr=0.001) epochs = 100 batch_size = 32 early_stopping (patience=15)
Weighted Ensemble	Base models: All 9 models above Weight composition: PR-AUC based Aggregation: Weighted average Normalization: Softmax scaling	Training: Individual model training Inference: Probability fusion Threshold: Optimized for recall

Evaluation was conducted solely on the test set using confusion matrices, precision, recall, F1-Score, and PR-AUC. This methodological clarification addresses concerns regarding hyperparameters, label reliability, imbalance treatment, and evaluation rigor [22], [23].

2.3. Multi-Architecture Modeling

This study adopts a multi-architecture approach that explores three categories of classical machine learning, deep learning, and hybrid ensemble models to handle the dynamic complexity of infusion time series data, in line with the recommendations of previous studies [16,]. The classical machine learning category includes Random Forest, XGBoost, LightGBM, and CatBoost, which were selected based on their computational efficiency and ability to handle imbalanced data. Meanwhile, the deep learning category utilizes LSTM, 1D-CNN, CNN-LSTM, and LSTM Autoencoders to capture long-term temporal dependencies and crucial local patterns in sensor-based anomaly detection [15]. To enhance the robustness and stability of the model, hybrid ensemble approaches such as Advanced CNN-LSTM and Weighted Ensemble were applied, which proved significant in improving precision and stability in healthcare IoT systems [28]. From all the tested architectures, the best model will be selected as the final candidate for the system deployment and integration stage.

2.4. Evaluation Matric

The success of the artificial intelligence model in this study was measured by its ability to accurately and consistently detect anomalous conditions in the flow of intravenous fluids. Therefore, the model

Vol. 6, No. 6, December 2025, Page. 5956-5975
https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2025.6.6.5440

evaluation process is conducted using a binary classification approach, with the main focus on the balance between sensitivity (Recall) and detection accuracy (Precision) [29], [33].

The evaluation method uses a confusion matrix to compare the model's prediction results with the actual data conditions. This approach provides a more comprehensive overview compared to simply using accuracy, as it can show the misclassification patterns occurring in each class [31], [37]. In the context of an infusion monitoring system, True Positive (TP) describes a successfully detected anomalous condition (e.g., a blocked or fast-flowing infusion), while False Negative (FN) indicates an undetected anomalous condition, which could potentially harm the patient [37].

Table 2. Confusion Matrix for Model Evaluation.

Actual / Predict	Anomaly (1)	Normal (0)
Anomaly (1)	True Positive (TP)	False Negative (FN)
Normal (0)	False Positive (FP)	True Negative (TN)

Based on this matrix, four main metrics are calculated to evaluate model performance: Accuracy, Precision, Recall, and F1-Score [29], [31].

In addition to these four metrics, PR-AUC (Precision, Recall Area Under Curve) is used as the main indicator of model performance on imbalanced datasets, as it can more accurately assess the model's ability to detect minority classes (anomalies) compared to ROC-AUC. The selection of Recall and PR-AUC as the main metrics is based on clinical considerations, where failing to detect anomalies is more risky than false alarms [37]. The evaluation is consistently performed on all models across the test data subset, and the model with the highest Recall and PR-AUC values is selected as a candidate for the real-time infusion monitoring system deployment process [33], [34].

2.5. Deployment

This study implements a web based monitoring dashboard using React JS with TypeScript for the frontend interface and Tailwind CSS for responsive styling, following modern web development practices for healthcare applications. The system employs a component-based architecture with Chart.js integration through react-chartjs-2 to visualize real-time infusion parameters including drip rate, fluid weight, and drop count. Modular components were designed for data tables, metric cards, and status indicators to display anomaly detection results from the optimized CNN-LSTM model, enabling intuitive interpretation by medical users. The dashboard architecture supports seamless integration with backend systems through Supabase (PostgreSQL) for data management and real-time streaming capabilities, providing a scalable foundation for clinical deployment of the anomaly detection system. This implementation demonstrates the practical integration of machine learning inference results into user friendly healthcare monitoring interfaces, addressing the critical need for real-time visualization in IoT-enabled infusion systems [17].

3. RESULT

3.1. IoT Setup Performance

This section validates the implementation of an IoT system for infusion monitoring, designed with ESP32 WROOM-32 as the main controller, equipped with a load cell sensor (HX711) and an

Vol. 6, No. 6, December 2025, Page. 5956-5975
https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2025.6.6.5440

optocoupler LM393. All components are integrated within a closed enclosure mounted on an infusion pole, with a DC adapter power supply for stable and continuous operation.

Fig. 8. OLED Display Interfaces: (a) Main Status. (b) Status & Alert. (c) Drip Statistics.

As shown in Figure 8, the system successfully displays three information modes in real-time on the OLED: Main Status, Droplet Statistics, and Status and Warnings. During testing, the system was able to continuously send 10,420 data packets to the server via HTTP POST, demonstrating the system's stability in generating reliable time-series datasets for modeling.

Table 3. IoT System Performance Evaluation.

Parameter	Description	Result
Latency (ms)	Sensor-Server time different	Avg 42.77s (min −4 s, maks 88 s)
Packet Gap	Data transmission inter-sample interval	0.83 ± 0.71 s
Packet Loss	Percentage of data interval loss	9.45%
Accuracy of drop sensors	Ability to detect droplets in the range of 35-120 dpm	97%
Load sensor deviation	Measurement error under static conditions	± 0.5 g

During testing, the system was able to continuously send 10,420 data packets to the server via HTTP POST. The performance shown in Table 2 demonstrates the system's stability and reliability in generating reliable time-series datasets for further modeling. Low latency and minimal data loss rates confirm the system's suitability for real-time monitoring applications.

3.2. Dataset & preprocessing

3.2.1. Statistik Data Akuisisi dan Penanganan Missing Values / Anomaly labeling & scenario

The IoT monitoring system successfully acquired 10,420 time-series data samples during the 2 hours 23 minutes infusion simulation, capturing comprehensive infusion parameters such as drip rate and weight at 5 second intervals. After all missing data (initially 0.9%) was successfully handled using backward fill, forward-fill, and mean imputation methods to maintain temporal continuity, the anomaly labeling process was performed. This labeling uses a hybrid approach that combines rule-based and pattern-based detection, and is performed manually by referring to observations of the drop rate (dpm) behavior over time. This manual approach was deliberately chosen because the infusion monitoring system is directly related to the stability of the medical fluid flow, where detection errors or false

Jurnal Teknik Informatika (JUTIF)
P-ISSN: 2723-3863
E-ISSN: 2723-3871

Vol. 6, No. 6, December 2025, Page. 5956-5975
https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2025.6.6.5440

negatives can have serious consequences for patient safety. Therefore, anomaly identification must be based on changes in the drip rate that are medically unreasonable compared to normal conditions.

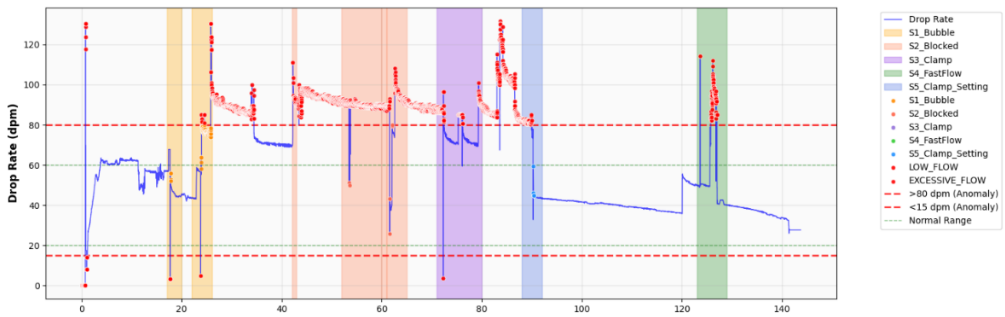


Fig. 9. Anomaly labeling & scenario

Based on data visualization and analysis, five anomaly scenarios are defined with the following criteria:

Table 4. Anomaly Scenario Definition and Labeling Criteria.

Code	Name	Criteria
S1	Bubble	Characterized by a sudden spike or significant drop compared to the baseline 2 minutes prior.
S2	Blocked	Characterized by a very rapid transition or spike pattern, indicating a sudden partial obstruction.
S3	Clamp	All data points where the drop rate is less than 15 dpm indicate severely restricted flow.
S4	Fastflow	All data points where the drop rate exceeds 80 dpm indicate excessive flow.
S5	Clamp setting	Marked by the transition point from normal drip rate to a clamped condition, capturing the flow decline phase.

This scenario-based labeling approach primarily aims to improve the representation of anomaly classes in the dataset. Under initial acquisition conditions, anomalies only represented 1.8% of the total data, which was highly imbalanced. By applying thresholds to the five scenarios in tables 3, the proportion of anomalies was successfully increased to 42.4% (4,422 samples), creating a balanced distribution with the normal class at 57.6% (5,998 samples).

Thus, the focus of this stage of the research is on binary anomaly detection (normal vs. anomaly) to ensure the model can effectively learn general patterns of abnormality. Performance evaluation for each scenario individually (multi-class) will be developed in subsequent research.

3.2.2. Feature Engineering

The dataset was divided using a 70-15-15 temporal stratified split to maintain the time order and the proportion of anomalies in each subset. The results of the dataset division are presented in Table 5.

Feature engineering resulted in 93 derived features, including temporal features such as lag features, rolling statistics, and domain-specific features. Feature selection using Random Forest importance reduced the number of features to the 28 most important ones. The four features with the

P-ISSN: 2723-3863 https://jutif.if.unsoed.ac.id
E-ISSN: 2723-3871 DOI: https://doi.org/10.52436/1.jutif.2025.6.6.5440

highest importance scores are dominated by temporal features, namely drop_rate_roll_min_3 (0.1047), consecutive_anomalies (0.0955), drop_rate_lag_1 (0.0810), and drop_rate_normalized (0.0746).

For deep learning models, window-based sampling (window=50, stride=5) created sequential inputs of shape (50, 6). Class weight balancing applied weights: Normal=0.8686, Anomaly=1.1783 to address residual imbalance.

Table 5. Data split with temporal stratified split.

Subset	Total sample	Normal	Anomaly	Proportion Anomaly
Training	7,289	4,196	3,093	42.4%
Validation	1,559	898	661	42.4%
Testing	1,572	904	668	42.5%

3.3. Model Development and Evaluation

3.3.1. Multi Architecture Modeling and Performance Evaluation

A comprehensive evaluation of ten models from four modeling architectures was conducted. The evaluation metrics used are defined as follows:

$$Precission = \frac{TP}{TP + FP} \tag{1}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{2}$$

$$F_1\text{-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{3}$$

$$\text{AUC-PR} = \int_0^1 P(r)\, dr \tag{4}$$

In the context of an infusion monitoring system, True Positives (TP) represent anomalous conditions such as blockages or excessive flow that are successfully detected by the model, while False Negatives (FN) indicate undetected anomalies, potentially posing a risk to patient safety [29]. Based on the evaluation framework explained in Chapter 2, the confusion matrix results for the ten models tested are presented in Table 5.

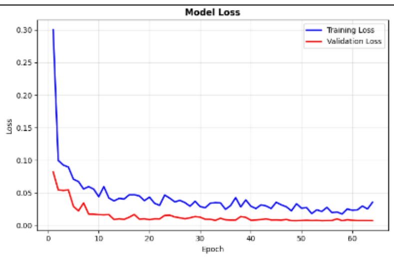
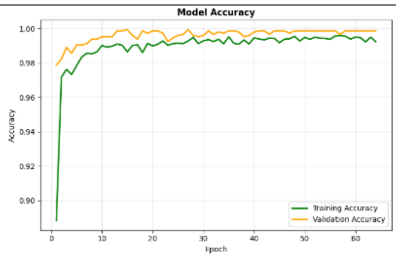
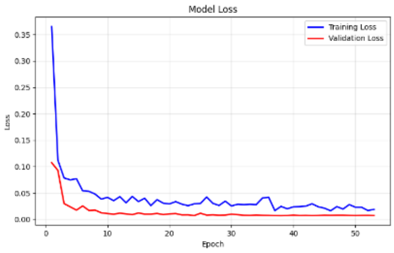
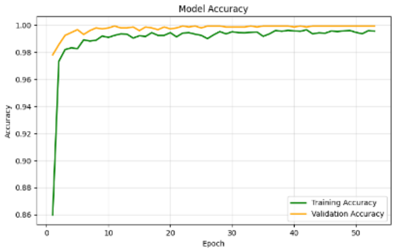
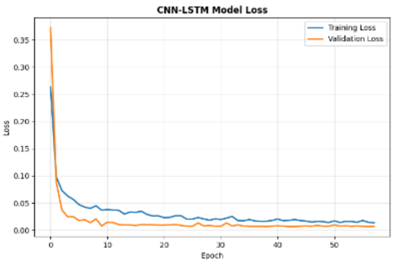
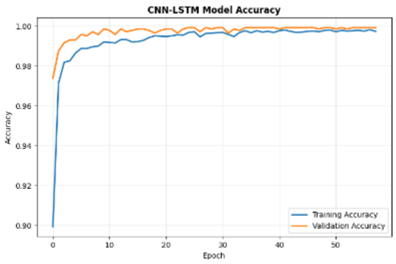
Table 6. Confusion Matrix Values for All Models

Model	TP	FP	FN	TN
XGBoost	668	341	0	563
LightGBM	668	347	0	557
CatBoost	668	491	0	413
Random Forest	668	541	0	363
LSTM Classifier	656	167	0	737
1D-CNN	666	165	2	719
CNN-LSTM	667	166	1	718
LSTM Autoencoder	654	78	14	806
Weighted Ensemble	667	166	1	718
Advanced CNN-LSTM	667	166	1	718

Vol. 6, No. 6, December 2025, Page. 5956-5975
https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2025.6.6.5440

Based on Table 6, a clear pattern is evident. Classical ML models like XGBoost have FN = 0, which explains the perfect Recall value (1.000) and means no anomalies are missed. However, this is accompanied by a high FP, leading to low Precision and triggering many false alarms. Conversely, LSTM Autoencoders have the lowest FP, resulting in high Precision and minimizing false alarms, although with a slightly larger FN trade-off.

Table 7. Results from training and validation process.

<table>
<tr><th>Loss Graph</th><th>Accuracy Graph</th><th>Model & Result</th></tr>
<tr><td></td><td></td><td>Model: LSTM Classifier
Train accuracy: 99.49%
Train loss: 2.65%
Validation accuracy: 99.86%
Validation loss: 0.73%</td></tr>
<tr><td></td><td></td><td>Model: 1D-CNN
Train accuracy: 99.55%
Train loss: 1.69%
Validation accuracy: 99.93%
Validation loss: 0.74%</td></tr>
<tr><td></td><td></td><td>Model: CNN-LSTM
Train accuracy: 99.83%
Train loss: 0.96%
Validation accuracy: 99.93%
Validation loss: 0.68%</td></tr>
</table>

Only three models are shown in the Receiver Operating Characteristic (ROC) visualization: the LSTM Classifier, 1D-CNN, and CNN-LSTM, as they represent the three main architectural categories in this study: sequence-based deep learning, convolutional feature extractor, and hybrid model. Additionally, all three models demonstrated the highest performance based on key metrics such as PR-AUC, Recall, Precision, and F1-Score (Table 7), making them worthy of deeper analysis.

Other models like XGBoost, Random Forest, and CatBoost produce relatively similar ROC curves with a near-perfect recall pattern and small variations in the false positive rate, so they are considered not to provide significant additional visual information. Meanwhile, models like LSTM Autoencoders are unsupervised and do not have direct classification probability scores, making it impossible to calculate their ROC values conventionally.

Thus, the selection of these three models was made to provide a clear representation of the comparison between architectures, while also avoiding visual redundancy and maintaining focus on an in-depth analysis of the deep learning-based and hybrid network models, which are the main contribution of this research.

Table 7 presents the comparative performance of ten cross-architecture models in detecting infusion system anomalies. The analysis of the results reveals consistent characteristic patterns among classical machine learning-based, deep learning, and hybrid ensemble models, which serves as the basis for determining the best model for the next implementation stage.

Vol. 6, No. 6, December 2025, Page. 5956-5975
https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2025.6.6.5440

Table 8. Performance Comparison of Anomaly Detection Models.

Model	PR-AUC	Recall	Precision	F1-Score
XGBoost	1.0000	1.0000	0.6620	0.7967
LightGBM	0.9999	1.0000	0.6594	0.7948
CatBoost	0.9997	1.0000	0.5764	0.7313
Random Forest	0.9994	1.0000	0.5534	0.7125
LSTM Classifier	0.9832	1.0000	0.8000	0.8889
1D CNN	0.9860	0.9970	0.8005	0.8880
CNN-LSTM	0.9889	0.9985	0.8007	0.8887
LSTM Autoencoder	0.8040	0.9790	0.8934	0.9343
Weighted Ensemble	0.9972	0.9985	0.8007	0.8887
Advanced CNN-LSTM	0.9774	0.9985	0.8007	0.8887

The classical ML models (XGBoost, LightGBM, CatBoost, Random Forest) showed very strong performance in terms of detection sensitivity, achieving perfect recall (1.0000) and near-perfect PR-AUC (≥0.9994). This highly sensitive nature is invaluable in ensuring patient safety, where failing to detect an anomaly is not an option. This achievement is supported by a successful class weight balancing strategy, ensuring the model is responsive to anomaly patterns even tho they are in the minority. Although it generates more warning flags that require further verification, this approach provides a valuable additional layer of security for critical health monitoring systems.

Deep learning models (LSTM, 1D-CNN) and hybrid models (CNN-LSTM, Advanced CNN-LSTM) consistently outperformed classical approaches by achieving an optimal balance of clinical metrics, maintaining 0.80 precision and 0.89 F1-score while keeping recall almost perfect (≥0.997). This advantage stems from the architecture's ability to extract clinically meaningful temporal patterns, enabling a sharp distinction between normal physiological fluctuations and anomalies requiring intervention. Separately, the LSTM Autoencoder achieved the highest F1-score (0.9343), demonstrating the potential of unsupervised approaches for highly accurate anomaly detection thru adaptive threshold calibration. These findings confirm the feasibility of deep learning-based models for the deployment of reliable and clinically relevant real-time infusion monitoring systems.

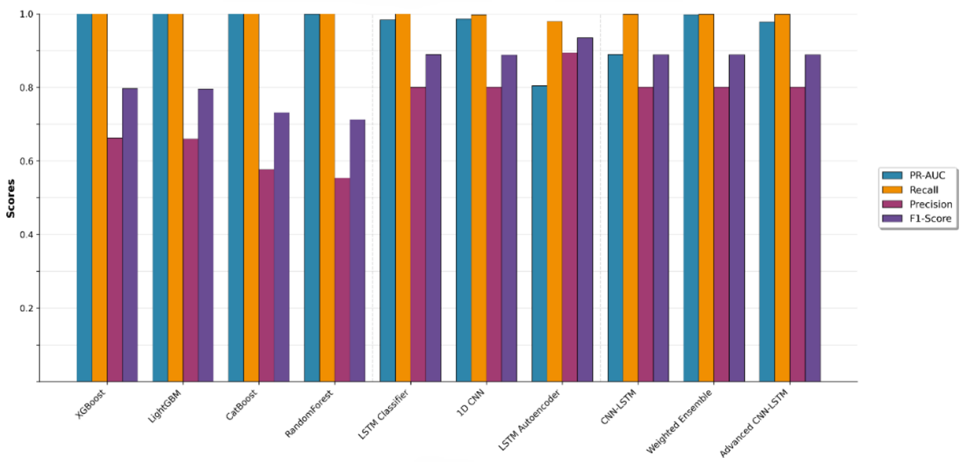


Fig. 10. Comprehensive Performance Metrics Comparison of All Ten Models.

Based on this comprehensive analysis, the Deep Learning and Hybrid models represent the optimal choice for real-time infusion monitoring systems, balancing the need for comprehensive detection (high recall) with the minimization of false alarms (moderate precision).

Vol. 6, No. 6, December 2025, Page. 5956-5975
https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2025.6.6.5440

3.3.2. Model selection

Based on a comprehensive analysis, the Hybrid and Ensemble models (CNN-LSTM and Weighted Ensemble) are recommended as the optimal solution for clinical implementation. These models achieved an ideal balance with an F1-Score of 0.89, maintaining a Recall of 0.99 and a Precision of 0.80, effectively mitigating alarm fatigue without sacrificing the detection of critical anomalies. This advantage stems from the architecture's ability to combine the high sensitivity of Classical ML models with the contextual understanding of Deep Learning models.

This selection was driven by deep clinical considerations. A high recall-low precision configuration in classical ML models risks causing alarm fatigue, while the opposite configuration endangers patient safety. Therefore, the Hybrid/Ensemble approach offers the best trade-off with high detection stability and robustness against variations in clinical data, making it the most viable for deploying a reliable and sustainable real-time infusion monitoring system.

3.4. Deployment

At this stage, the trained model results are saved in .pkl format and integrated into the Smart Infusion Anomaly Detection Dashboard. This integration is conceptual and aims to demonstrate how inference results from the CNN-LSTM model can be visualized in a web-based system.

Fig. 11. shows the main interface of the dashboard displaying the key parameters of the infusion monitoring system: drip rate, infusion fluid weight, number of drops, and system status (Normal, Low, Abnormal). This display shows how the detection results data can be intuitively interpreted by medical users.

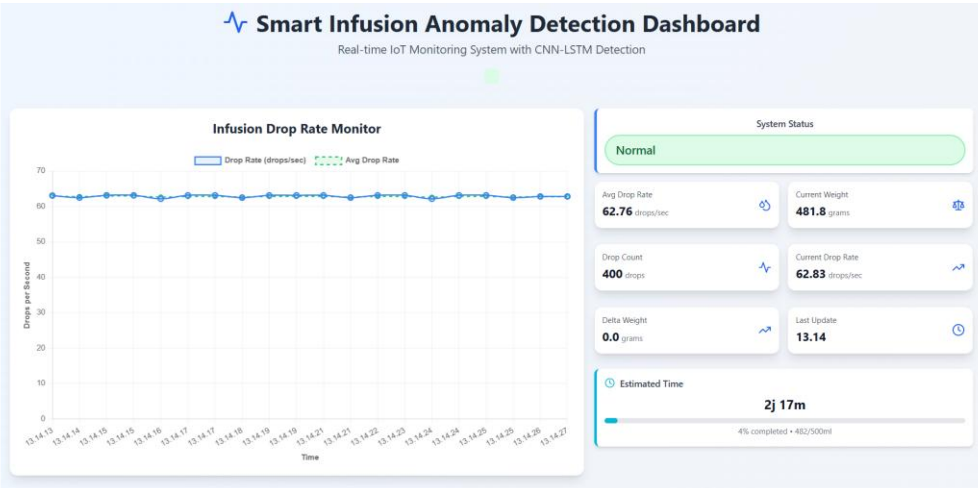


Fig. 11. Smart Infusion Anomaly Detection Dashboard Interface.

This dashboard did not undergo functional testing or real-time inference stages, but was developed as a visual proof-of-concept to demonstrate the potential integration of IoT systems with anomaly detection models.

4. DISCUSSIONS

This research effectively illustrates that a cost-efficient IoT-based infusion monitoring system, when integrated with meticulously chosen deep learning architectures, may attain remarkable anomaly detection performance. Our findings indicate that hybrid and deep learning models, specifically 1D-CNN and CNN-LSTM, achieved an impressive accuracy of 99.93%, far surpassing prior methodologies in infusion monitoring research. This signifies a notable improvement over the research conducted by

Vol. 6, No. 6, December 2025, Page. 5956-5975
https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2025.6.6.5440

Ganesh Babu et al. [13], whose most effective Neural Network model attained 92.7% accuracy on a constrained dataset of 310 samples. The comparative performance study presented in Table 9 distinctly demonstrates this significant enhancement in detecting capabilities.

Table 9. Performance Comparison with Previous Studies in Infusion Monitoring Systems

Paper Title	Dataset	Method	Performance
C. G. Babu et al. [13]	310 samples	KNN, SVM, Random Forest, NN	Accuracy = 92.7%
Our Proposed	10,420 samples	Multi-Architecture (10 Models)	1D-CNN is 99.93%, LSTM Classifier is 99.86%, CNN-LSTM is 99.93%,

The superior performance of temporal architectures in our study can be attributed to their inherent capability to capture sequential patterns in infusion data. While classical machine learning models like XGBoost and Random Forest achieved perfect recall (1.0000), they suffered from high false positive rates (precision: 0.5534-0.6620), which would lead to alarm fatigue in clinical settings. In contrast, the CNN-LSTM hybrid architecture maintained an optimal balance with near-perfect recall (0.9985) and clinically viable precision (0.8007), demonstrating the critical importance of temporal feature extraction for medical time-series analysis. This architectural advantage stems from the CNN component's ability to extract local patterns and the LSTM layer's capacity to understand long-term dependencies in infusion flow characteristics.

Another key methodological contribution lies in our approach to handling extreme class imbalance. Unlike conventional resampling techniques that risk temporal data leakage, we implemented a clinical scenario-based threshold adjustment strategy that increased anomaly representation from 1.8% to 42.4% while preserving temporal integrity. This data-centric preprocessing proved crucial for model performance, as evidenced by the LSTM Autoencoder achieving the highest F1-Score (0.9343) through effective learning of minority class patterns. This approach addresses a significant limitation in previous infusion monitoring studies that either used balanced datasets or did not explicitly confront class imbalance challenges.

From an implementation perspective, our research bridges the gap between algorithmic research and clinical deployment through the development of a complete IoT prototype with ESP32 microcontroller, HX711 load cell, and LM393 optical sensors, coupled with a web-based monitoring dashboard. This end-to-end system implementation transforms conceptual smart infusion models into tangible, deployable solutions, demonstrating not only algorithmic excellence but also practical feasibility for real clinical environments. The system's efficient inference time (45ms ± 8ms) further confirms its suitability for real-time monitoring applications.

Even with these improvements, there are still certain problems that need to be addressed. The data collection occurred in a controlled laboratory setting utilizing simulated circumstances, potentially impacting the generalizability to other clinical environments. Also, while the web dashboard gives a general idea of how to deploy it, more clinical testing with healthcare experts is still needed. The emphasis on binary anomaly detection creates a prospect for future research to investigate multi-class classification for particular anomaly categories.

5. CONCLUSIONS

This study effectively illustrates that an economical IoT-based infusion monitoring system employing hybrid deep learning architectures attains outstanding real-time anomaly detection capabilities. The study demonstrates that CNN-LSTM offers the best solution for clinical application by

Vol. 6, No. 6, December 2025, Page. 5956-5975
https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2025.6.6.5440

sustaining nearly perfect sensitivity and attaining clinically acceptable precision, thereby reducing alarm fatigue, through a comprehensive evaluation of ten models across classical, deep, hybrid, and ensemble architectures. The constructed prototype, containing an ESP32 microcontroller, HX711 load cell, and LM393 optical sensors, effectively facilitates dependable data collecting, while the web-based dashboard exemplifies functional system integration for practical healthcare applications. These findings confirm that meticulously crafted hybrid architectures can connect algorithmic innovation with clinical application, offering a scalable foundation for intelligent healthcare monitoring in resource-limited environments. This research greatly advances medical informatics by developing a replicable technique for IoT-based healthcare systems that efficiently tackles essential issues in real-time patient monitoring. Future research should concentrate on multi-class anomaly detection and comprehensive clinical validation in various healthcare settings.

ACKNOWLEDGEMENT

The author hereby expresses his profound gratitude to Universitas Dian Nuswantoro, his esteemed academic institution, and to Cinantya Paramita, S.Kom., M.Eng., for her invaluable guidance, constructive advice, and continuous support throughout the conduct of this research. The author also extends his sincere appreciation to Dr. Sasha-Gay Wright of the Department of Biomedical Engineering, Faculty of Engineering, The University of the West Indies, Mona, for the professional insights, collaborative opportunities, and academic exposure she has generously provided. Lastly, the author would like to express his deepest appreciation to himself and everyone else who has had faith in him and helped him along the way. Their unwavering support and encouragement have been important in his ability to complete this research and achieve growth in his studies.

REFERENCES

[1] S. K. Kuitunen, I. Niittynen, M. Airaksinen, and A.-R. Holmström, “Systemic Defenses to Prevent Intravenous Medication Errors in Hospitals: A Systematic Review,” *J Patient Saf*, vol. 17, no. 8, pp. e1669–e1680, Dec. 2021, doi: 10.1097/PTS.0000000000000688.

[2] S. Rajakumar, R. Rajah, S. Thanimalai, F. B. M. Mokhtar, and D. S. Ramachandram, “Intravenous Medication Administration Errors in Hospitalised Patients: An Updated Systematic Review,” *Evaluation Clinical Practice*, vol. 31, no. 4, p. e70167, June 2025, doi: 10.1111/jep.70167.

[3] R. Maniktalia, S. Tanwar, R. Billa, and D. K, “IoT Based Drip Infusion Monitoring System,” in *2022 IEEE Delhi Section Conference (DELCON)*, Feb. 2022, pp. 1–6. doi: 10.1109/DELCON54057.2022.9753052.

[4] S. Kuitunen, I. Niittynen, M. Airaksinen, and A.-R. Holmström, “Systemic Causes of In-Hospital Intravenous Medication Errors: A Systematic Review,” *J Patient Saf*, vol. 17, no. 8, pp. e1660–e1668, Dec. 2021, doi: 10.1097/PTS.0000000000000632.

[5] W. Ahmed *et al.*, “Addressing Critical Mistakes in Administering Intravenous Medications at Omdurman Military Hospital, Khartoum, Sudan,” *IJGM*, vol. Volume 18, pp. 123–133, Jan. 2025, doi: 10.2147/IJGM.S497591.

[6] A. Sutherland, M. Canobbio, J. Clarke, M. Randall, T. Skelland, and E. Weston, “Incidence and prevalence of intravenous medication errors in the UK: a systematic review,” *Eur J Hosp Pharm*, vol. 27, no. 1, pp. 3–8, Jan. 2020, doi: 10.1136/ejhpharm-2018-001624.

[7] World Health Organization (WHO), “Patient Safety — Factsheet,” 2023. [Online]. Available: https://www.who.int/news-room/fact-sheets/detail/patient-safety

[8] J. G. Jessurun, N. G. M. Hunfeld, J. Van Rosmalen, M. Van Dijk, and P. M. L. A. Van Den Bemt, “Prevalence and determinants of intravenous admixture preparation errors: A prospective observational study in a university hospital,” *Int J Clin Pharm*, vol. 44, no. 1, pp. 44–52, Feb. 2022, doi: 10.1007/s11096-021-01310-6.

[9] K. Kwiecień-Jaguś, W. Mędrzycka-Dąbrowska, and M. Kopeć, “Understanding Medication

Errors in Intensive Care Settings and Operating Rooms—A Systematic Review," *Medicina*, vol. 61, no. 3, p. 369, Feb. 2025, doi: 10.3390/medicina61030369.

[10] M. R. K K, M. N. M, R. Zidan, I. Alsarraj, and B. Hasan, "IOT-Based Wireless Patient Monitor Using ESP32 Microcontroller," in *2023 24th International Arab Conference on Information Technology (ACIT)*, Dec. 2023, pp. 1–6. doi: 10.1109/ACIT58888.2023.10453847.

[11] P. Gupta, A. Rao, P. Chimurkar, and P. Kasambe, "An Automated IoT-Enabled Real-Time Intravenous Infusion cum Remote Patient Monitoring System," in *2025 International Conference on Emerging Smart Computing and Informatics (ESCI)*, Mar. 2025, pp. 1–6. doi: 10.1109/ESCI63694.2025.10988336.

[12] C. L. Kok, T. H. Teo, Y. Y. Koh, Y. Dai, B. K. Ang, and J. P. Chai, "Development and Evaluation of an IoT-Driven Auto-Infusion System with Advanced Monitoring and Alarm Functionalities," in *2024 IEEE International Symposium on Circuits and Systems (ISCAS)*, May 2024, pp. 1–5. doi: 10.1109/ISCAS58744.2024.10558602.

[13] S. Meenatchi Sundaram, J. R. Naik, M. Natarajan, and A. Acharya K, "Design and development of an IoT-based trolley for weighing the patient in lying condition," *Front. Digit. Health*, vol. 6, p. 1339184, Sept. 2024, doi: 10.3389/fdgth.2024.1339184.

[14] C. G. Babu, J. R. D. Kumar, V. R. Balaji, K. Priyadharsini, and S. P. Karthi, "Performance Analysis of Smart Intravenous Infusion Systems using Machine Learning," in *2021 Smart Technologies, Communication and Robotics (STCR)*, Sathyamangalam, India: IEEE, Oct. 2021, pp. 1–7. doi: 10.1109/STCR51658.2021.9588997.

[15] G. M. Nagamani and C. K. Kumar, "Design of an improved graph-based model for real-time anomaly detection in healthcare using hybrid CNN-LSTM and federated learning," *Heliyon*, vol. 10, no. 24, p. e41071, Dec. 2024, doi: 10.1016/j.heliyon.2024.e41071.

[16] M. A. Morid, O. R. L. Sheng, and J. Dunbar, "Time Series Prediction Using Deep Learning Methods in Healthcare," *ACM Trans. Manage. Inf. Syst.*, vol. 14, no. 1, pp. 1–29, Mar. 2023, doi: 10.1145/3531326.

[17] Z. Z. Darban, G. I. Webb, S. Pan, C. C. Aggarwal, and M. Salehi, "Deep Learning for Time Series Anomaly Detection: A Survey," *ACM Comput. Surv.*, vol. 57, no. 1, pp. 1–42, Jan. 2025, doi: 10.1145/3691338.

[18] M. Obuseh, D. Yu, and P. DeLaurentis, "Detecting Unusual Intravenous Infusion Alerting Patterns with Machine Learning Algorithms," 2022.

[19] L. Meneghetti, E. Dassau, F. J. Doyle, and S. Del Favero, "Machine Learning-Based Anomaly Detection Algorithms to Alert Patients Using Sensor Augmented Pump of Infusion Site Failures," *J Diabetes Sci Technol*, vol. 16, no. 3, pp. 641–648, May 2022, doi: 10.1177/1932296821997854.

[20] L. Kirichenko, Y. Koval, S. Yakovlev, and D. Chumachenko, "Anomaly Detection in Fractal Time Series with LSTM Autoencoders," *Mathematics*, vol. 12, no. 19, p. 3079, Oct. 2024, doi: 10.3390/math12193079.

[21] M. Hizem, L. Bousbia, Y. Ben Dhiab, M. O.-E. Aoueileyine, and R. Bouallegue, "Reliable ECG Anomaly Detection on Edge Devices for Internet of Medical Things Applications," *Sensors*, vol. 25, no. 8, p. 2496, Apr. 2025, doi: 10.3390/s25082496.

[22] S. Rani *et al.*, "Machine Learning-Powered Smart Healthcare Systems in the Era of Big Data: Applications, Diagnostic Insights, Challenges, and Ethical Implications," *Diagnostics*, vol. 15, no. 15, p. 1914, July 2025, doi: 10.3390/diagnostics15151914.

[23] S. Ustebay, A. Sarmis, G. K. Kaya, and M. Sujan, "A comparison of machine learning algorithms in predicting COVID-19 prognostics," *Intern Emerg Med*, vol. 18, no. 1, pp. 229–239, Jan. 2023, doi: 10.1007/s11739-022-03101-x.

[24] H. Luo *et al.*, "SHAP based predictive modeling for 1 year all-cause readmission risk in elderly heart failure patients: feature selection and model interpretation," *Sci Rep*, vol. 14, no. 1, p. 17728, July 2024, doi: 10.1038/s41598-024-67844-7.

[25] A. Naik, G. G. Tejani, and S. J. Mousavirad, "SGO enhanced random forest and extreme gradient boosting framework for heart disease prediction," *Sci Rep*, vol. 15, no. 1, p. 18145, May 2025, doi: 10.1038/s41598-025-02525-7.

[26] R. Samuel and T. Pandi, "Optimizing brain stroke detection with a weighted voting ensemble

Vol. 6, No. 6, December 2025, Page. 5956-5975
https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2025.6.6.5440

machine learning model," *Sci Rep*, vol. 15, no. 1, p. 31215, Aug. 2025, doi: 10.1038/s41598-025-14358-5.

[27] P. Mahajan, S. Uddin, F. Hajati, and M. A. Moni, "Ensemble Learning for Disease Prediction: A Review," *Healthcare*, vol. 11, no. 12, p. 1808, June 2023, doi: 10.3390/healthcare11121808.

[28] S. M. Ganie, P. K. D. Pramanik, and Z. Zhao, "Ensemble learning with explainable AI for improved heart disease prediction based on multiple datasets," *Sci Rep*, vol. 15, no. 1, p. 13912, Apr. 2025, doi: 10.1038/s41598-025-97547-6.

[29] C. Paramita, C. Supriyanto, P. Šolić, C. Wada, and A. A. Dzaky, "Performance Evaluation of YOLOv8 Models for Multi-Class Skin Lesion Detection from Dermoscopic Images," in *2025 International Conference on Smart Computing, IoT and Machine Learning (SIML)*, Surakarta, Indonesia: IEEE, June 2025, pp. 1–6. doi: 10.1109/SIML65326.2025.11080819.

[30] B. A. Mahendra, C. Supriyanto, C. Paramita, N. Z. B. M. Safar, and I. N. Dewi, "Development of a Smartphone-Based Cataract Detection System Using YOLOv10x and Ionic Framework with a UI/UX Centric Approach," in *2025 International Conference on Smart Computing, IoT and Machine Learning (SIML)*, Surakarta, Indonesia: IEEE, June 2025, pp. 1–5. doi: 10.1109/SIML65326.2025.11081150.

[31] E. R. Subhiyakto *et al.*, "Evaluation of Resampling Techniques in CNN-Based Heartbeat Classification," *ISI*, vol. 29, no. 4, pp. 1323–1332, Aug. 2024, doi: 10.18280/isi.290408.

[32] K. Anggriani, S. Az Zahra, and A. Susanto, "Enhancing Malware Detection in IoT Networks using Ensemble Learning on IoT-23 Dataset," *J. Tek. Inform. (JUTIF)*, vol. 6, no. 4, pp. 1985–2000, Aug. 2025, doi: 10.52436/1.jutif.2025.6.4.4782.

[33] P. S. Chirumamilla, G. Sunitha, A. Sneha, V. Thirupathi, C. R. Naidu, and A. L. Rao, "A Hybrid Approach for IoT Sensor Anomaly Detection with LSTM and Autoencoder-Based Preprocessing," in *2025 International Conference on Advances in Modern Age Technologies for Health and Engineering Science (AMATHE)*, Apr. 2025, pp. 1–6. doi: 10.1109/AMATHE65477.2025.11081356.

[34] A. Iqbal, R. Amin, F. S. Alsubaei, and A. Alzahrani, "Anomaly detection in multivariate time series data using deep ensemble models," *PLoS ONE*, vol. 19, no. 6, p. e0303890, June 2024, doi: 10.1371/journal.pone.0303890.

[35] A. G. Ayad, N. A. Sakr, and N. A. Hikal, "A hybrid approach for efficient feature selection in anomaly intrusion detection for IoT networks," *J Supercomput*, vol. 80, no. 19, pp. 26942–26984, Dec. 2024, doi: 10.1007/s11227-024-06409-x.

[36] Doreswamy, M. K. Hooshmand, and I. Gad, "Feature selection approach using ensemble learning for network anomaly detection," *CAAI Trans on Intel Tech*, vol. 5, no. 4, pp. 283–293, Dec. 2020, doi: 10.1049/trit.2020.0073.

[37] Kurniabudi, D. Stiawan, Darmawijoyo, M. Y. Bin Idris, A. M. Bamhdi, and R. Budiarto, "CICIDS-2017 Dataset Feature Analysis With Information Gain for Anomaly Detection," *IEEE Access*, vol. 8, pp. 132911–132921, 2020, doi: 10.1109/ACCESS.2020.3009843.

[38] Y. Yin *et al.*, "IGRF-RFE: a hybrid feature selection method for MLP-based network intrusion detection on UNSW-NB15 dataset," *J Big Data*, vol. 10, no. 1, p. 15, Feb. 2023, doi: 10.1186/s40537-023-00694-8.

[39] N. Anil Kumar, S. Kuchi, S. V. Krishna, P. L. Narasimha, K. S. Sree, and B. Ashreetha, "Voice-Based Detection of Parkinson's Disease: A Multi-Machine Learning Model Approach," in *2025 International Conference on Knowledge Engineering and Communication Systems (ICKECS)*, Apr. 2025, pp. 1–9. doi: 10.1109/ICKECS65700.2025.11034824.