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Preventing the Drug Consumptions among the Growing Generation using AI Technology

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ABSTRACT

An international public health concern is the rising prevalence of drug misuse among the younger population, especially among students and young people. Addiction to drugs has far-reaching consequences that affect not only the addict but also their loved ones and the community. Responding to drug use rather than proactively preventing it is a common goal of conventional approaches. A major challenge in drug misuse is the lack of empirical evidence supporting the new technological approaches effectiveness, including Artificial Intelligence (AI) and Internet of Things (IoT). Current monitoring systems, do not leverage advanced technologies and often fail to detect early indicators in time. The proposed solution aims to fill this gap, although further empirical data is required to fully validate the effectiveness of AI and IoT technologies. This research investigates a novel approach to monitor and prevent drug misuse by using AI and IoT technology. The goal is to create a system that can identify the first physical signs of drug use and notify parents or guardians so they can intervene quickly. The proposed approach utilizes an IoT device with sensors to track vital signs. AI algorithms process and analyse this data to identify anomalies that may indicate drug usage. The technology notifies the parent or guardian's mobile app in real-time if it detects unusual symptoms. Continuous learning from data enhances the accuracy of the system's predictions. The AI-driven IoT system successfully identifies irregularities in the tracked physiological data, including unusual temperature swings indicative of drug use. The system's ability to generate and transmit alerts to guardians enabled early intervention. Impressive precision, accuracy and recall accompanied the system's ability to detect possible drug intake. This study shows that AI and the IoT have the ability to identify drug misuse in its early stages. However, the effectiveness of the proposed solution remains to be fully verified through empirical testing and data collection. The technology may provide a preventative measure against drug addiction by sending real-time notifications.

Keywords:
AI technology; drug abuse prevention; early detection; guardianship alerts; IoT system

1. Introduction

Medication adherence is a significant concern for physicians, healthcare systems, as well as other stakeholders such as insurance companies, given the prevalence of drug abuse among senior citizens.

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Patients who must take many medications at once often fail to do so [1]. IoT technology is essential to smart drug delivery systems in the modern age of technology. The discipline is still in its initial stages, but it holds enormous promise for enhancing drug therapy effectiveness, safety and patient adherence. In order to monitor and analyse the patient's health parameters in real-time, IoT-based drug delivery systems use cutting-edge equipment, smart sensors and sophisticated tools [2].

Deep learning (DL) algorithms and artificial neural networks, are responsible for bringing the science to its current state. Drug repositioning, pharmacophore modelling, ligand-based virtual screening, structure-based virtual screening, peptide synthesis, drug monitoring as well as release, quantitative structure-activity relationship and drug activity are some of the drug discovery processes that have utilized DL and Machine Learning (ML) algorithms [3]. This work develops and verifies a DL-based model, deep-Avpiden, to enhance the efficiency of categorization and identification of antiviral peptides (AVPs). The model does a better job than both classic long short-term memory networks (LSTMs) as well as recurrent neural networks (RNNs) at capturing long-term dependencies and parallel computing. Employing temporal convolutional networks (TCNs) achieves this [4].

Smart cities (SC) aim to improve the quality of life for their citizens by offering a range of intelligent applications, including intelligent transportation, smart finance and industry 4.0. By recording transactions in a distributed ledger that is transparent, irreversible, secure and decentralized, blockchain technology (BCT) enables SC to provide a greater level of security [5]. In the US, drug overdoses accounted for a disproportionate share of injuries and fatalities that year (2021). Throughout the overdose pandemic, concerns about solitary drug use and solitary overdose fatalities have persisted, requiring particular attention. Overdose detection technologies (ODT), have allowed for quicker reactions to overdose incidents, particularly in cases involving individuals who take drugs alone [6].

Using privacy, transparency and compatibility as its guiding principles, an article presents PharmaChain, a distributed Hyperledger fabric framework. Users can store data on and off the blockchain with this system, enabling faster and more secure transactions and smart contracts can track the origin of data. The security measures include a 33% node attack, hash data encryption and double signing using the elliptic curve digital signature algorithm [7]. To ensure that hospitalized patients get high-quality medications in a secure environment, another research introduces an IoT-Enhanced Medication Quality Assurance system. It continuously monitors the storage conditions of medications using IoT technology [8].

Mensah *et al.,* [9] determined whether the Food and Drugs Act of Ghana provides the medical regulatory body with the necessary legislative framework and policy instruments to assess risks and supervise software devices based on AI. International regulatory problems and case studies of medical AI systems highlight the difficulties regulators face today. Certain parts of the Act examine in detail definitions, standards for safety as well as effectiveness evidence, rules for modifications to authorized devices, along with post-market authorities.

Akram *et al.,* [10] discussed about the distributors, producers, suppliers of raw materials, regulators, pharmacies, healthcare facilities and patients in the pharmaceutical supply chain (PSC). An effective PSC traceability system is required to identify the present and all prior owners of the product because of the product's complexity as well as transaction flows. Digitizing the trace along with track process assures product quality and greatly enhances regulatory supervision. Utilizing BCT for medication traceability might lead to the creation of a decentralized database that is trustworthy, transparent, immutable and responsible across the PSC. Blockchain is a software-based technology that chronologically organizes as well as stores transactions in a block structure.

Trautmann *et al.,* [11] explores the obstacles that PCSs encounter, such as the problem of medicine counterfeiting and explores the potential solutions that digital technologies can offer. Also included are assessments of potential dangers posed by digital technologies. Experts interviewed stakeholders in the PSC in the first round. This evaluated the collected material using qualitative content analysis. Aside from the lack of openness, it became clear that the supply chain players had significant personal interests and that there were varying degrees of digitalization adoption. One other thing that stands out is how focused the industry is on paper. Despite this, the selected specialists hold optimistic expectations for the future of digital technologies. By integrating blockchain with other technologies like AI as well as IoT, this can make pharma supply chains more efficient, trustworthy and traceable.

Rane *et al.,* [12] highlighted about Artificial General Intelligence (AGI) that can really transform Industry 4.0, Society 5.0 and beyond, marking a huge leap forward from narrow AI. In Industry 4.0, AGI will make possible fully autonomous fabrication processes, which would optimize supply chains and personalize goods very efficiently. This expects Industry 5.0 to emerge from the integration of AGI and human intelligence, fostering a more collaborative and sustainable industrial environment that prioritizes human-centric innovation and well-being. With its intelligent solution tailoring to the requirements of people and communities, Society 5.0 has a vision of peacefully combining cyberspace and physical space but ignores the potential role AGI may play in addressing the complex social concerns of healthcare, education and urban management.

Ahmed *et al.,* [13] described drug-related tragedies such as sexual assaults and car accidents are on the rise globally. There are important workplaces where drug use is common, leading to major safety. This has led to an increase in the importance of point-of-care diagnostic and monitoring technologies, particularly in areas such as onsite criminal investigation, clinical diagnostics, workplace drug testing as well as roadside drug detection for the prevention of drunk driving. Table 1 shows the details of the existing works.

Table 1
Existing works review

Papers and authors	Method	Advantages	Limitations
Mensah *et al.*, [9]	AI systems	Evaluates whether the Food and Drugs Act of Ghana provides the medical regulatory body with sufficient policy instruments and a statutory foundation to assess risks and supervise AI-based software products.	-
Akram *et al.*, [10]	Blockchain technology	Digitizing the track and trace process assures product quality and greatly improves regulatory oversight.	No details about pharmaceutical goods.
Rane *et al.*, [12]	AGI	Prevent undesirable outcomes.	Do not address the deep ethical implications of AGI.

The lack of preventive measures that may identify early indications of drug abuse prior to addiction taking hold is a significant gap in present drug prevention initiatives. While reactive measures are a foundation of conventional drug prevention strategies, they overlook the need for real-time monitoring technologies that can pick up on even the most minor physiological changes caused by drug abuse. Additionally, there is an absence of real-time health marker tracking systems that incorporate AI and the IoT. Timely treatments may prevent drug usage from escalating and these technologies have the ability to provide continuous, data-driven insights into a person's health. The research significance presents an innovative use of AI along with the IoT for real-time drug misuse detection as well as monitoring, which holds significant importance. The research enables parents and guardians to promptly intervene, providing a preventative approach. It adds to the growing corpus of knowledge about the application of wearable technology in health monitoring and behavioural analysis. This research could potentially promote early intervention, thereby reducing the long-term societal impact of drug abuse. Here are the primary objectives of this research:

i. The system aims to aggressively identify early symptoms of drug intake among young individuals by designing and implementing an IoT-based system that integrates AI algorithms. Monitoring physiological markers (such as heart rate as well as body temperature) that are often impacted by drug usage will be the main aim of this system.
ii. To guarantee continuous identification of aberrant symptoms associated with drug misuse, it is necessary to provide real-time monitoring of the user's physiological data using wearable IoT devices. By using this tack, it hopes to spot problems before they get much worse.
iii. In the event that the system identifies questionable physiological patterns, it should quickly notify parents or guardians via an automatic alarm system. These notifications will enable early action, crucial in preventing further drug usage.
iv. Determine how well the system detects aberrant health behaviour by integrating AI and IoT technologies; evaluate its accuracy and reliability in recognizing patterns of drug addiction.
v. This study could serve as a model for future advancements in wearable health technologies that aim to detect various health issues early.

The work organization is stated here: Section 2 discusses the proposed methodology. Section 3 presents the details regarding the results attained as well as the discussions of the research along with some limitations of the present research. The references come next and Section 4 concludes the work.

2. Proposed Methodology

Through the integration of AI and IoT technologies, the drug abuse detection system offers real-time monitoring and early intervention for drugs. Data Collection, Data Preprocessing, Data Analysis, Alert Generation, as well as Guardian Response are the five main steps in the process. The first step of the system is to gather physiological data from wearable IoT sensors, such as body temperature and heart rate. In real time, these sensors record critical metrics and send the readings to an online database or mobile app for study using Wi-Fi or Bluetooth. The design of the technology closely monitors indications such as heart rate and body temperature, which are known to fluctuate during drug consumption. Pre-processing preprocess the gathered raw data to standardize the measurements and eliminate noise. Noise filtering, addressing missing values and normalization are the preprocessing procedures. It cleans up the data to facilitate analysis, minimizing errors from the environment or sensors.

After preprocessing, data enters an AI model. The AI analyses physiological patterns to identify anomalies that may indicate drug abuse. Signs of drug use include, an abnormal increase in heart rate or temperature. To identify out-of-the-ordinary changes from the norm, the system employs anomaly detection methods. The discovery of an anomaly triggers a system alert. When the system discovers an aberrant physiological pattern, it instantly transmits an alarm to the guardian's mobile application, providing real-time alerts. Critical circumstances trigger urgent alerts, with the intensity of the alert corresponding to the magnitude of the anomaly. Upon receiving the alarm, the guardian promptly assesses the situation and takes appropriate action. Depending on the seriousness, this might include monitoring the person's behaviour or calling emergency services. Additional help, such as connections to emergency services or health care providers, can be available via the mobile app. Figure 1 shows the proposed flow.

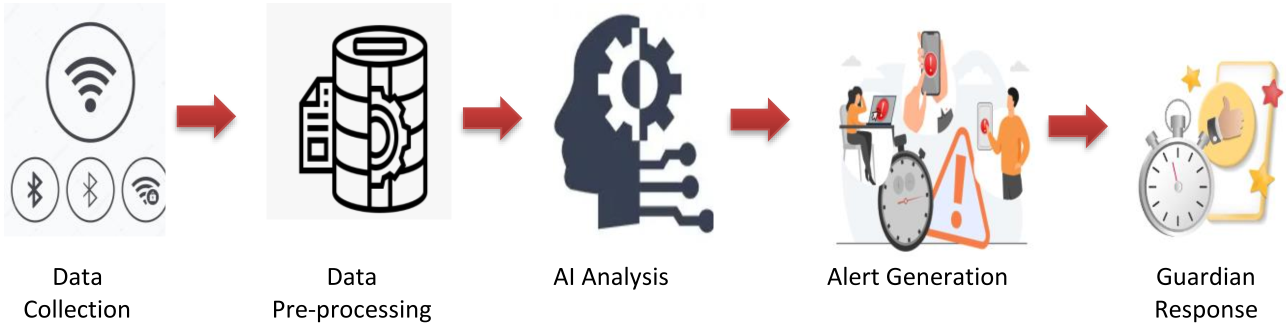

Fig. 1. Proposed flow

2.1 Data Collection

Through embedded IoT sensors in wearable devices or mobile chips, the system initially gathers real-time physiological data from the person. By monitoring certain physiological markers, these sensors may detect possible indications of drug abuse. Since drug ingestion often alters vital signs like temperature and heart rate, these metrics are the primary focus of this study. These sensors constantly collect data and send it to the cloud or mobile app for analysis. Some examples of such sensors include heart rate monitors, accelerometers and temperature sensors. A temperature sensor measures the skin's temperature, which may change with drug ingestion. A rise in core temperature is a common side effect of several drugs, including stimulants. A heart rate monitor measures the number of heart beats per minute. The heart rate may be either tachycardia (high) or bradycardia (low) depending on the drug. Usually, a central database or mobile app receives the data via Wi-Fi or Bluetooth. The temperature (T) formula is in Eq. (1).

$$T(t) = T_{initial} + \Delta T \tag{1}$$

Where $T(t)$ represent temperature at time t, $T_{initial}$ is the baseline temperature and ΔT represent change in temperature due to drug influence. This work determines the variations in heart rate by Eq. (2).

$$HR(t) = HR_{initial} + \Delta HR \tag{2}$$

Where $HR(t)$ represent heart rate at time t, $HR_{initial}$ is the baseline heart rate and ΔHR represent change in heart rate. Privacy and consent-related ethical considerations are at the core of developing and deploying AI-driven surveillance systems. Before collecting any physiological data from a child, permission from a parent or guardian must be acquired. The use, storage and protection of the data must also be explained in straightforward and unambiguous language to the minors and their guardians.

2.2 Data Preprocessing

Inconsistencies and noise are common in the raw data obtained from the sensors. To make sure the data is clean and ready for analysis, data preparation is crucial. Several procedures, including feature extraction, normalization, addressing missing data and noise filtering, are involved in this stage. It may use standard methods like median filtering, Kalman filtering or moving averages on the data to eliminate outliers attributed to environmental influences, sensor faults or other external variables. When merging data from many sensors that use different measurement scales, normalization is a must. This standardizes the data scale so that all sensors may provide similar results for analysis. Table 2 displays for Preprocessing steps.

Table 2
Pre-processing table

Parameter	Raw Value	Pre-processed Value	Notes
Body Temperature	37.8°C	0.3°C	Normalized to baseline
Heart Rate	110 bpm	100 bpm	Noise filtered
Movement (Activity)	500 steps	0.25 (normalized)	Rescaled for analysis

2.3 AI Analysis

This research uses three ML algorithms like Random Forest, Multi-Layer Perceptron (MLP) and CatBoost to train AI models using pre-processed data [14].

2.3.1 CatBoost (Categorical Boosting)

CatBoost, a robust gradient boosting algorithm, excels in handling both numerical and categorical variables in data. Without requiring human preparation, CatBoost efficiently handles categorical features, in contrast to typical gradient boosting techniques. The CatBoost algorithm uses a gradient boosting framework to construct a network of decision trees. It uses residual mistakes as a learning tool to repeatedly reduce a loss function. Ordered boosting is a specialized method that it employs to lessen the impact of overfitting and improve generalization to previously unexplored data. Let $F(x)$ be the prediction function and y the observed target. The model updates its prediction $F(x)$ using the following iterative update rule in Eq. (3):

$$F_{t+1}(x) = F_t(x) + \eta \,.\, \Delta F_t(x) \tag{3}$$

Where $F_t(x)$ represent prediction at iteration t, η is the learning rate and $\Delta F_t(x)$ is the residual error corrected at iteration t.

2.3.2 Multi-Layer Perceptron (MLP)

A specific kind of artificial neural network called a MLP has several layers of nodes or neurons. Activation functions introduce non-linearity into each fully connected layer. Classification, regression and anomaly detection are some uses for MLPs. Two or more hidden layers, an output layer and an input layer make up an MLP. Network layers often use activation functions like ReLU, Sigmoid or Tanh to process the weighted sum of inputs. The output layer generates the prediction based on the analysed data. The Eq. (4) for a single neuron in the hidden layer is:

$$h_i = \sigma\left(\sum_{j=1}^{n} w_{ij} x_j + b_i\right) \tag{4}$$

Where h_i refers output of the i-th neuron, x_j refers input to the neuron from the previous layer, w_{ij} represent weight between the j-th neuron of the previous layer and the i-th neuron, b_i is the bias term and $\sigma(.)$ are the activation function. Typically, this work calculates the prediction for the output layer as follows in Eq. (5):

$$y_{pred} = \sigma(\sum_{i=1}^{m} w_i h_i + b) \tag{5}$$

Where y_{pred} is the predicted output (e.g., probability of drug abuse detection), w_i is the weights of the final layer, h_i represent outputs of the hidden layer and b is the bias term. Particularly in cases when there are complicated and non-linear correlations between physiological parameters, MLP is able to find intricate patterns in the data.

2.3.3 Random forest

An ensemble learning technique, Random Forest constructs several decision trees and then integrates them to get a more reliable and accurate prediction. Both classification and regression issues, such as finding patterns in large datasets like physiological measures, benefit greatly from its use. The training phase of Random Forest produces a vast number of decision trees, which is how the model operates. To train their trees, it uses a completely random subset of features and data, with full replacement. To arrive at the final prediction, it averages all the trees (for regression) or vote on the majority (for classification). Ultimately, the prediction is founded on Eq. (6):

$$\hat{y} = \frac{1}{N} \sum_{i=1}^{N} f_i(x) \tag{6}$$

Where $\hat{y}$ represents predicted class label, $f_i(x)$ are the prediction from the i-th decision tree and N denotes number of trees in the forest. This study trains the trees using bootstrapped data subsets to ensure their diversity and prevent overfitting and use a random subset of features to select the splits at each node. One advantage of Random Forest is its feature significance calculation capabilities. This lets the system determine which physiological parameters, such as body temperature as well as heart rate, are most useful for identifying drug abuse. The feature importance $Imp(f_j)$ is computed as the average decrease impurity (e.g., Gini impurity) across all trees where the feature is used for splitting in Eq. (7):

$$Imp(f_j) = \frac{1}{N} \sum_{i=1}^{N} \Delta Impurity_i(f_j) \tag{7}$$

Where $\Delta Impurity_i(f_j)$ represent decrease in impurity when feature f_j is used in the i-th tree. This research trains the model using physiological data from past known drug abuse cases. Locating data anomalies and trends that can suggest drug usage is an important part of the training process [15]. Rapid heart rate and high temperature are signs of stimulant drug use, while a low heart rate and low temperature suggest opioid use. To classify whether the patient is likely to be under the effect of drugs, the AI model makes use of these patterns. After that, the z-score technique, along with other ML algorithms, may be used for anomaly detection in Eq. (8):

$$Z = \frac{X - \mu}{\sigma} \tag{8}$$

Where Z denotes z-score, X refers observed value, μ denotes mean of the data and σ is the standard deviation. A z-score higher than a threshold (e.g., 2 or 3) indicates an anomaly, such as drug use.

2.4 Alert Generation

If the AI model detects an anomaly, it sends out an alert. Through a mobile app or device, the system notifies the parent or guardian in real time. This alert may suggest immediate action, such as seeking medical assistance or monitoring the individual's behaviour and may include specifics regarding the observed anomaly, such as abnormal heart rate and body temperature. This system can configure various alert types based on the severity of the anomaly. An example of a minor anomaly would be a warning message; an example of a severe anomaly would be an alarm notice in the event of a significant rise in heart rate or temperature. Before sending an alert, it must meet the following conditions in Eq. (9):

$$Anomaly\ Score > Threshold \tag{9}$$

The AI model's output calculates the anomaly score, while data from earlier testing and training establishes the threshold. Table 3 shows the Alert levels.

Table 3
Alert levels

Alert Level	Threshold	Action
Low	1.5	Warning notification
Medium	2.5	Immediate attention
High	3.0	Emergency alert

2.5 Guardian Response

As soon as they receive the alert, the parent or guardian must respond. The person's conduct may require close monitoring or immediate medical care. In addition to the primary functions, the mobile app could provide supplementary capabilities that allow the guardian to contact healthcare providers via chat or directly access emergency services. Timely action is crucial at this point. There is a higher probability of avoiding more drug usage or reducing its negative consequences if a guardian can react quickly to the alert. Figure 2 displays the Guardian Response.

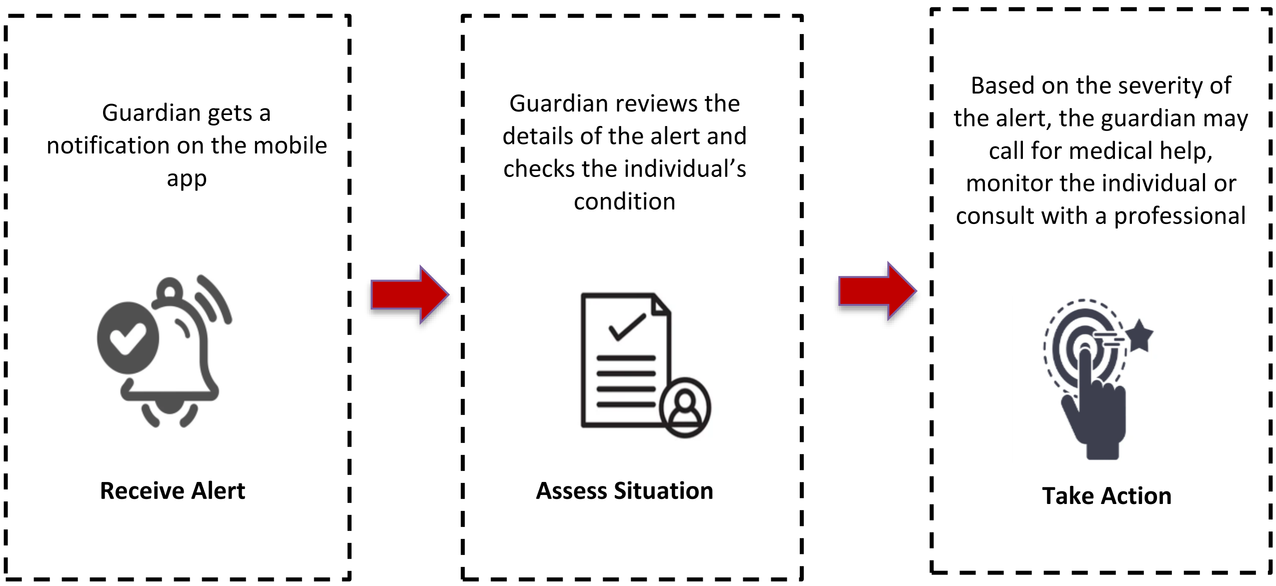

Fig. 2. Guardian response

This study gets the alert when the body temperature reaches 39.5°C and the heart rate reaches 125 bpm. Follow these steps: reach out to medical professionals, dial emergency services and monitor the patient's condition closely.

3. Results

This section shows the outcomes of contrasting three ML algorithms—CatBoost, MLP and Random Forest—for detecting drug abuse using body data collected from IoT sensors. This also provide a general description of the dataset that is used for training and assessing these algorithms, going over how the data is chosen and pre-processed to produce useful findings.

3.1 Dataset Description

Individual physiological data, with an emphasis on factors often affected by drug usage, formed the basis of the dataset utilized in this investigation. This work gathered the data using wearable IoT sensors, which measure vital signs like heart rate, temperature and other biomarkers affected by drug usage. In order for the system to understand the distinctions in physiological patterns between these two groups, the dataset includes both healthy people and those with documented drug abuse difficulties. The important elements of the dataset are:

i. Monitor core body temperature (°C) consistently using a thermometer.
ii. A heart rate monitor determines the heart rate in beats per minute (bpm).
iii. Motion (steps): A motion detector records the number of steps, providing information on the level of activity.
iv. Additional Parameters: In certain circumstances, sensors for skin conductivity, oxygen levels and blood pressure may also be present.

To label the data, this research uses two categories:

i. Normal: No evidence of substance abuse was found.
ii. Drug Abuse: Physiological signs of drug usage, such as sharp changes in body temperature or irregular heart rates.

Then two sets from the dataset are created, one for training and one for testing. To make sure the data was fair, it included both healthy and drug-abusing people in equal numbers. This pre-processed the data by applying normalization, noise filtering and missing value imputation before feeding it into the models.

3.2 Model Training and Evaluation Metrics

Using the dataset, this work train three ML algorithms: Random Forest, CatBoost and MLP. F1 score, area under the ROC curve (AUC), precision, accuracy as well as recall are some of the common categorization metrics used to assess each model. The ratio of accurately predicted occurrences to the total instances is how accuracy gauges the model's overall accuracy in Eq. (10).

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{10}$$

Where TP signify True Positive (correctly predicted positive instances), TN denote True Negative (correctly predicted negative instances), FP represent False Positive (incorrectly predicted positive) and FN denote False Negative (incorrectly predicted negative). Precision calculates the proportion of true positive predictions to all predictions in Eq. (11).

$$Precision = \frac{TP}{TP+FP} \tag{11}$$

The proportion of accurately detected genuine positive cases is measured by recall in Eq. (12).

$$Recall = \frac{TP}{TP+FN} \tag{12}$$

An F1 score strikes a balance between recall and accuracy by taking their harmonic mean in Eq. (13).

$$F1 - score = 2.\frac{Precision.Recall}{Precision+Recall} \tag{13}$$

A larger area indicates a better performance of the model. This work uses AUC as a performance metric to analyse classification issues at various threshold settings.

3.3 Comparative Results of the Algorithms

Table 4 below summarizes the results of the models tested as well as trained on the same dataset.

Table 4
Comparison results

Algorithm	Accuracy	Precision	Recall	F1-Score	AUC
CatBoost	92.3%	91.5%	93.0%	92.2%	0.97
MLP	88.5%	87.0%	90.5%	88.7%	0.94
Random Forest	90.0%	89.0%	91.5%	90.2%	0.95

CatBoost demonstrated superior performance compared to Random Forest and MLP algorithms in every parameter. It achieved the greatest F1 score (92.2%), recall (94.0%), precision (91.5%) and accuracy (92.3%). Particularly when it came to generalizing on unseen data, CatBoost's improved performance was due in large part to its built-in regularization algorithms and its capability to manage categorical features. Good at handling unbalanced or noisy datasets, this method was probably more resilient. With an AUC of 0.94 and an accuracy of 88.5%, MLP's performance was somewhat worse than CatBoost. The intricate nature of the neural network made the MLP model difficult to avoid overfitting, requiring extensive hyperparameter adjustment and careful regularization to achieve optimal results. On the other hand, MLP showed strong performance, especially in recall, suggesting it may successfully identify cases of drug abuse. The results were satisfactory for Random Forest, which achieved an AUC of 0.95 and an accuracy of 90%. Although CatBoost achieved somewhat better overall performance, the model demonstrated a decent trade-off between recall and accuracy. Random Forest's interpretability and feature significance may aid in a better understanding of the main physiological signs that contribute to drug abuse detection.

3.4 Feature Importance and Insights

When it comes to determining which physiological indicators are most suggestive of drug abuse, CatBoost and Random Forest ability to offer feature significance is a great benefit. Table 5 below displays the feature significance as determined by the models.

Table 5
Feature significance

Feature	CatBoost Importance	Random Forest Importance
Body Temperature	45%	40%
Heart Rate	35%	38%
Movement	15%	18%
Other Parameters	5%	4%

While levels of activity may decrease when under the influence of drugs, the findings indicate that core body temperature and heart rate are the most important indicators of drug abuse. Although CatBoost, MLP and Random Forest are the primary AI algorithms used in this work to identify drug abuse in its early stages, there is a vast diversity of AI-based technologies and approaches that might be used to address this issue. To better understand patterns in physiological data, for instance, the system may benefit from using deep learning models like RNNs or convolutional neural networks (CNNs). Furthermore, adaptable models that change in response to user actions over time might be developed using reinforcement learning. To provide a more all-encompassing strategy for drug prevention, future research might build on this work by combining this and other AI methods.

4. Conclusion and Future Work

Comparative findings show that, when it comes to identifying drug abuse from physiological data, the CatBoost algorithm is superior to both Random Forest and MLP. The experimental findings show that the IoT technology powered by AI may reliably identify physiological markers of drug abuse. CatBoost has shown promising results as a technique for detecting drug usage, with higher accuracy, precision, recall and AUC. In addition, it is feasible to monitor vital signs like heart rate and temperature for early intervention due to the importance of these elements. To verify these results and improve the system's prediction skills, more empirical validation using bigger datasets and real-world testing is crucial. Future phases of this study will use a more diversified dataset, comprising different drugs and environmental circumstances, for additional testing. Adding additional sensors (for things like blood pressure and oxygen saturation) and enhancing its real-time prediction skills might improve the accuracy of the system. In order to better identify drug abuse in real time and avoid long-term harm to people, future work will also concentrate on strengthening the system's implementation via mobile applications or wearable devices for continuous monitoring.

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