

BioSentry: Real-Time Adverse Drug Reaction Monitoring and Detection

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Abstract— Adverse Drug Reactions (ADRs) continue to be a significant source of harm to patients and hospitalizations, whereas most pharmacovigilance centers are based on retrospective reporting or rule-based drug interaction screening. This paper introduces BioSentry, a real-time ADR monitoring system that combines Internet of Things (IoT) wearable sensors, computer vision, and artificial intelligence for early risk prediction during drug administration. A wearable module is designed to continuously monitor physiological signals such as heart rate, blood oxygen saturation, body temperature, blood pressure indicators, and skin conductance using MAX30102, DS18B20, BMP180, and GSR sensors. Simultaneously, visual inspection of facial expressions and emotions, pupil details, skin eruptions, and upper body posture is conducted by a mobile/webcam camera to identify visually observable ADR symptoms like discomfort, dizziness, flushing, or unusual motor activity. Multimodal information is combined and processed using machine learning algorithms to compare current values with patient-specific baselines and past ADR trends to identify risk levels as low, moderate, or high. Patient monitoring is triggered after each drug administration, allowing longitudinal monitoring across drug administration cycles and automatic notification to pharmacovigilance centers for high risk patients. The proposed solution aims to be cost-effective, non-invasive, and scalable for proactive and personalized drug safety monitoring.

Key Words: Adverse Drug Reactions, Clinical Decision Support Systems, Computer Vision, Internet of Things, Machine Learning, Multimodal Data Fusion, Patient Monitoring, Pharmacovigilance, Wearable Sensors.

1. INTRODUCTION

Adverse Drug Reactions (ADRs) continue to pose serious challenges to patient safety and healthcare systems worldwide, frequently leading to preventable complications, extended hospital stays, and increased treatment costs. Pharmacovigilance programs have been established to detect such events, but many still depend on delayed or voluntary reporting mechanisms, including manual notification approaches [2]. These processes often fail to capture early physiological changes and provide limited support for individualized patient monitoring. Clinical decision-support and alert-management systems have attempted to reduce medication-related risks [6]; however, most rely on static interaction rules or historical records rather than continuous observation of a patient's condition after drug intake. In recent years, artificial intelligence has played an expanding role in ADR research. Several studies have explored mining online discussions and clinical text to uncover adverse reactions using natural language processing and sentiment analysis techniques

[1], [3], [10]. More recent work has applied graph-based learning and self-supervised strategies to model drug-drug interactions and predict side effect risks [5], while large pharmacovigilance datasets have been analyzed using classical machine-learning methods combined with resampling strategies to estimate reaction severity [8]. Distributed computing platforms have further accelerated ADR signal detection at scale [7]. Although these approaches have significantly improved retrospective surveillance, they remain dependent on previously reported events and cannot directly reflect the patient's real-time physiological state during medication use. Internet of Things (IoT) technologies provide an opportunity to move ADR monitoring closer to real-world clinical settings through continuous sensing and connectivity. Early systems demonstrated that sensor-enabled infrastructures could assist in allergy and ADR identification [4], and real-time activity monitoring frameworks have been proposed for broader patient safety applications [9]. Nevertheless, most existing IoT-based healthcare platforms focus on a limited number of vital parameters and rarely incorporate visual symptom analysis or multimodal reasoning tailored specifically for detecting adverse drug effects. These limitations highlight several open challenges: first, the absence of structured monitoring aligned with medication schedules; second, the underutilization of computer vision to detect visible ADR symptoms such as facial distress, pupil changes, or skin reactions; and third, the lack of personalized models that learn from a patient's historical responses while directly supporting pharmacovigilance reporting. To address these gaps, this paper presents BioSentry, a real-time ADR monitoring framework that combines wearable IoT sensors, camera-based symptom analysis, and machine-learning algorithms for early risk assessment. The system initiates monitoring shortly after each drug dose, stores multimodal data throughout the treatment course, and categorizes reaction severity into low, moderate, or high levels. When high-risk patterns are identified, alerts are automatically forwarded to healthcare professionals or pharmacovigilance centers to enable rapid clinical response.

2. RELATED WORK

A. ADR Detection from Textual and Pharmacovigilance source

A substantial body of work has focused on extracting ADR signals from unstructured textual data such as social media posts and clinical notes. Wang et al. [1] proposed a quantum inspired Bi-LSTM model with attention mechanisms to recognize ADR-related expressions from online discussions, demonstrating improved performance over conventional sequence-learning methods. Li et al. [3] showed that incorporating emotional cues and domain knowledge could further enhance ADR detection, while Sweidan et al. [10] employed ontology-guided transfer learning using XLNet to classify ADR mentions at the sentence level. Together, these studies highlight the importance of language understanding and sentiment analysis in

pharmacovigilance. However, their dependence on retrospective textual data limits their ability to observe a patient's physical condition during active medication use. Large pharmacovigilance repositories have also been explored using machine-learning techniques. Sun et al. [7] introduced a distributed Spark-based framework combined with Bayesian models to accelerate ADR signal discovery, and Wei et al. [8] applied resampling strategies with classification algorithms to estimate drug-risk severity levels. More recently, ChandraUmakantham et al. [5] leveraged graph neural networks and self-supervised learning to capture complex drug-drug relationships and side-effect patterns. While these contributions strengthen large-scale ADR analytics, they primarily operate on historical reports and cannot support immediate, patient-level intervention

B. Reporting Systems and Clinical Decision Support

Efforts to improve ADR surveillance have also targeted reporting mechanisms within clinical workflows. Amit and Rataboli [2] proposed a drop-box-based approach to simplify ADR notification in hospital settings, addressing usability barriers but still requiring manual participation. Clinical decision-support systems have attempted to enhance medication safety by reducing unnecessary alerts and improving workflow efficiency. Lee et al. [6] described a real time adaptive alert-management system that adjusts notifications based on contextual information. Although such tools improve usability for clinicians, they are typically driven by predefined rules or electronic health records rather than by continuous physiological sensing..

C. IoT-Enabled Health Monitoring

IoT technologies have opened new possibilities for continuous health monitoring both inside and outside hospitals. Jara et al. [4] presented an early IoT-based pharmaceutical information system aimed at detecting allergies and ADRs, demonstrating the feasibility of distributed sensing infrastructures for medication safety. Activity-monitoring systems for patient protection, such as the wearable alert platform described by Aditya et al. [9], further illustrate how real-time data streams can support clinical care. Nevertheless, most existing IoT centered solutions monitor only a narrow set of vital parameters or movement patterns and do not include detailed visual symptom analysis or ADR-specific multimodal intelligence.

D. Summary and Research Gaps

Taken together, prior studies have made important contributions to ADR mining from text, large-scale pharmacovigilance analytics, IoT-based sensing, and clinical decision-support systems. Despite this progress, several challenges remain unresolved. First, many AI-driven ADR detection systems depend on retrospective data rather than real-time physiological measurements collected after medication intake. Second, visual indicators such as facial distress, pupil changes, or skin reactions—often among the earliest observable signs of ADRs—are rarely incorporated into automated platforms. Finally, existing systems seldom provide personalized, longitudinal modeling across full treatment courses while maintaining seamless integration with pharmacovigilance reporting processes.

3. PROPOSED METHODOLOGY

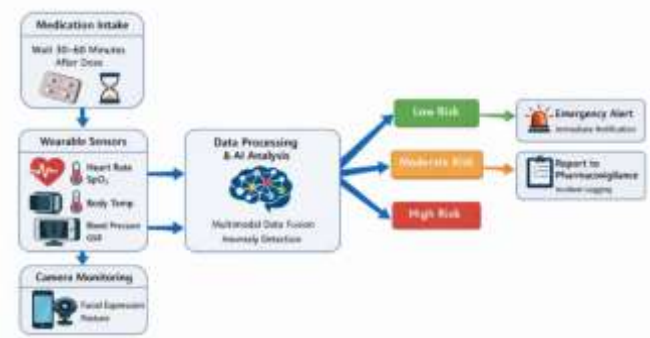


Fig 1. Workflow diagram of the proposed AI-IOT based ADR monitoring and Detection system.

A. System Overview The proposed

BioSentry framework is intended to facilitate the continuous and personalized monitoring of patients during the course of medication through the integration of wearable sensing, visual symptom analysis, and artificial intelligence-driven risk assessment. The approach adopted in the proposed framework follows a multimodal pipeline where physiological sensing and camera-based observation are acquired, synchronized, processed, and analyzed to identify early warning signs of adverse drug reactions

Fig. 1: End-to-end workflow of the proposed ADR monitoring and detection system. The workflow begins after the intake of medication, where the patient is monitored within a fixed time window of about 30-60 minutes post each medication intake. During this time, the wearable sensor module continuously monitors and records the patient's physiological signals such as heart rate, blood oxygen saturation (SpO2), body temperature, blood pressure indicators, and galvanic skin response (GSR). Simultaneously, a mobile device or webcam captures visual indicators such as facial expressions and upper body posture to detect external manifestations of discomfort or unusual behavior.

The recorded multimodal data streams are then sent to the backend system for real-time processing and artificial intelligence-driven analysis. Feature extraction and multimodal fusion algorithms combine physiological signals with visual features to detect anomalies against patient specific baseline models. The combined feature is then analyzed using machine learning algorithms to predict the likelihood and severity of possible adverse drug reactions.

Depending on the predicted severity, the system assigns patient risk levels as low, moderate, or high. Low-risk patients are continuously monitored, moderate-risk patients are recorded and submitted for pharmacovigilance analysis, and high-risk alerts are immediately sent to healthcare professionals for emergency clinical action.

B. Module Descriptions

• User Management Module

The system starts with a user management module that allows safe registration and login for patients, healthcare professionals, and pharmacovigilance staff. During the registration process, users are able to create accounts using the mobile or web interface, which is secured using encrypted

communication channels and role-based access control. Each user role is allowed access to only approved functions, which ensures that there is no overlap between patient monitoring, healthcare professional monitoring, and pharmacovigilance monitoring.

After the registration process, a personal profile is created for each patient, which holds demographic information, relevant medical history, known allergies, and medications

• Post-Dosage Monitoring Workflow

The monitoring process is triggered as soon as the patient records a drug intake via the application. A predefined observation period is started, during which physiological sensing and visual monitoring are enabled at the same time. This ensures that the data collected are aligned with the respective drug intake in time.

All data streams are time-stamped and sent securely to the backend platform for analysis

• Wearable Sensor Data Acquisition

A wearable device with multiple biomedical sensors constitutes the sensing layer of the system and is used to monitor physiological parameters that are often linked to ADRs. The MAX30102 sensor is used to measure heart rate and blood oxygen levels, and the DS18B20 digital thermometer is used to measure body temperature. The BMP180 sensor is used to measure atmospheric pressure, which serves as an indirect measure of blood pressure. A galvanic skin response sensor is used to monitor changes in skin conductance, which are often linked to stress or allergic reactions.

The sensor data is sampled at appropriate rates and filtered using digital preprocessing techniques to eliminate motion artifacts and environmental noise. Time stamps are added to the data to ensure synchronization with visual data streams and medication schedules

• Camera-Based Symptom Analysis

To identify any visible symptoms of ADRs, the system analyzes video feeds captured through a mobile front-facing camera or webcam. Facial landmarks are used to analyze expressions to determine discomfort or distress. Pupil features are analyzed to determine irregular pupil dilation, and skin areas are segmented to analyze rashes or flushing. Pose estimation algorithms are used to analyze upper body positioning and irregularities in movement such as tremors or instability. The visual features are mapped to numerical values and analyzed together with physiological data.

• Multimodal Data Fusion

Physiological and visual descriptions are then merged to create a unified feature representation that captures the current status of the patient. Temporal alignment is maintained by synchronized timestamps, and subject-specific normalization is used to account for individual variability. Feature-level fusion methods combine statistical vital sign descriptions with deep feature embeddings from vision models, enabling effective learning of correlations between modalities.

• AI Based Risk Prediction

The combined feature vectors are then analyzed through machine learning algorithms trained for anomaly detection and classification of ADR severity. Baseline profiles are developed for individual patients based on data collected from previous doses, and anomalies from the baseline are then assessed. Risk scores are then categorized into low, moderate, and high risk for

easier interpretation. Learning strategies adapt baselines based on new data available.

• Alerting and Pharmacovigilance Reporting

When high-risk patterns of ADRs are identified, automatic notifications are sent to healthcare professionals or pharmacovigilance teams via the application dashboard. Notifications contain summaries of deviations in vital signs, visual symptoms, and risk scores to facilitate quick clinical decisions. Aggregate and anonymous data can be exported for regulatory submissions and post-market drug surveillance.

• Data Storage and Privacy Protection

All data is stored in encrypted cloud storage with controlled access policies. Data sharing policies based on consent, audit trails, and anonymization tools are incorporated to meet healthcare data protection regulations. The system design is scalable to accommodate large patient bases and extended periods of monitoring.

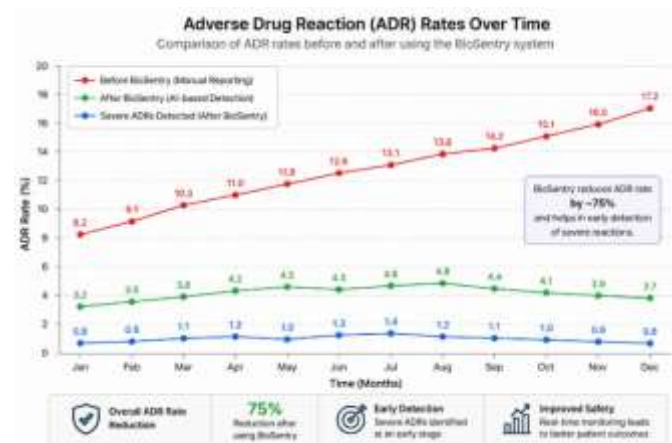


FIG-2: ADR risk chart

4. DESIGN ANALYSIS AND DISCUSSION

This section will analyze the design choices that go into the proposed BioSentry framework and will discuss what these choices mean from the perspective of real-time adverse drug reaction (ADR) detection. The design choices that will be analyzed include sensing hardware, vision-based monitoring, AI models, and system integration.

A. Multimodal Sensing Strategy

One of the key design decisions in the proposed system is the multimodal sensing approach, which combines wearable physiological sensing with visual symptom analysis. The symptoms of ADRs can be very diverse, including cardiovascular or heat regulation problems, dermatological reactions, and neurological symptoms. A single modality based approach may also result in incomplete or inaccurate detection of ADRs. The proposed system combines heart rate, oxygen saturation, skin conductance, temperature, and visual indicators such as facial distress and posture instability to leverage complementary information for robustness.

The fusion approach also makes the system less sensitive to noise in wearable sensors or temporary occlusions in the camera views. For example, even if the facial region is partially occluded, the system can still rely on physiological signals for risk assessment, and even if there are temporary motion artifacts in wearable sensors, the visual context can help alleviate these issues.

B. Event-Driven Monitoring and Personalized Baselines

Conventional reporting architectures and alerting mechanisms are centered around documentation after an event or decision support based on rules [2], [6]. The current design, on the other hand, follows an event-driven monitoring strategy that is triggered after every recorded intake of drugs, allowing synchronization with physiological changes over time. Baseline modeling for individual patients also sets the current framework apart from population-based strategies [5], [8], as it takes into account differences that frequently result in false alerts in population-based wearable monitoring solutions.

C. Edge-Cloud Deployment Strategy

Existing IoT solutions for ADR detection [4] and real time patient monitoring [9] demonstrate the viability of distributed sensing topologies, but offer little insight into large-scale analytics or cloud-based integration. The hybrid edge-cloud architecture presented here builds on these concepts by leveraging mobile devices for light preprocessing and offloading more complex multimodal reasoning to cloud-based services. While this approach improves scalability and enables rapid notification, it also relies on network connectivity, a problem that could be addressed in future versions with increased edge intelligence.

D. Learning Models and Clinical Interpretability

Graph neural networks and self-supervised learning approaches have been recently explored to capture the complex interactions of drugs and their side-effect risks [5], whereas sentiment-based language models have improved the extraction of ADRs from text [1], [3], [10]. With the aim of benefiting from these AI-based breakthroughs, the current system combines both anomaly detection and supervised learning classifiers to address the trade-off between the detection of new reactions and meaningful risk stratification. Interpretability is highlighted to promote clinician trust, as in adaptive alert management systems that aim to alleviate cognitive overload in clinical practice [6].

E. Privacy and Report Consideration

Manual reporting systems like the ADR drop-box method in [2] illustrate the need for accessibility in pharmacovigilance reporting, but do not consider the privacy issues involved with continuous sensing and video recording. Thus, the proposed system incorporates encryption, role based access control, and consent-driven data sharing throughout the user management pipeline. Additionally, the system's capability of producing structured summaries for pharmacovigilance centers extends previous reporting systems [2], but with a focus on automated, real-time data collection.

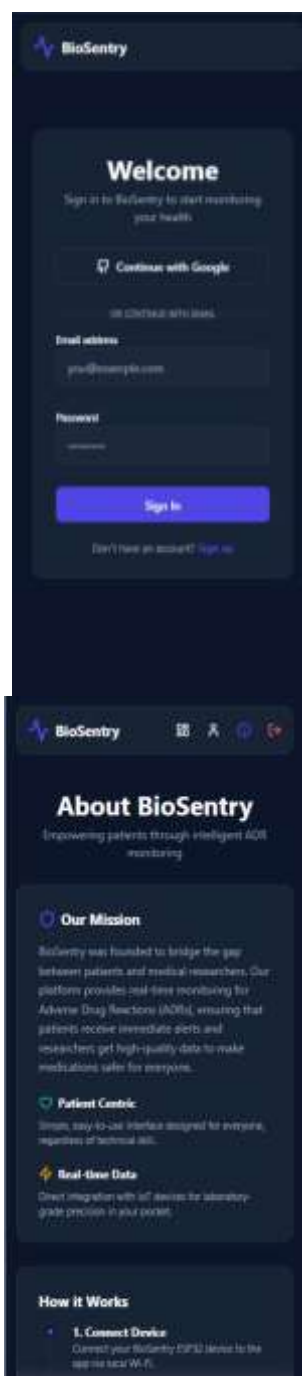


FIG 4.1 :Login page

FIG 4.2: About page



FIG 4.3: Questionnaire



FIG 4.4: Add medicine



FIG 4.7: Vitals Data

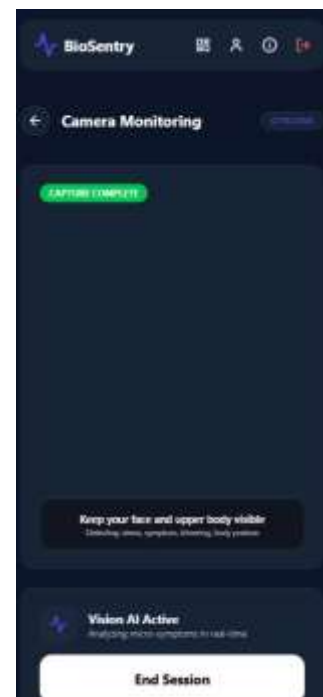


FIG 4.8: Camera Monitoring



FIG 4.5: Select Tablet device

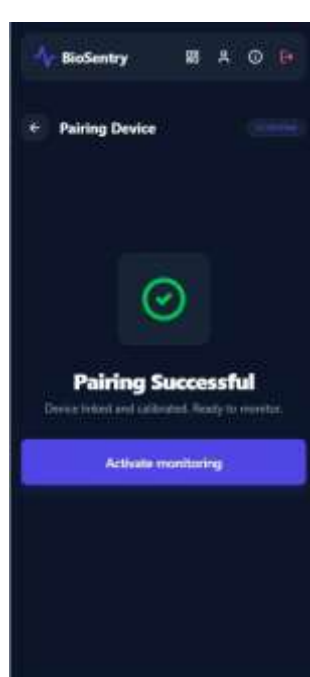


FIG 4.6: Pair

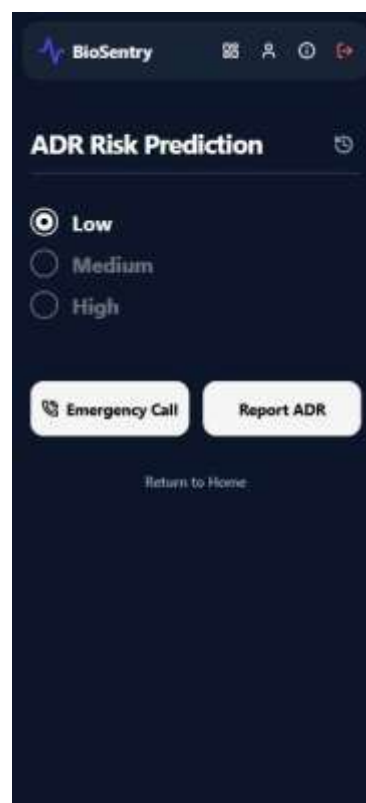


FIG 4.9: ADR risk

CONCLUSION AND FUTURE WORKS

This paper introduced BioSentry, an AI and IoT-based framework for real-time monitoring and early warning of adverse drug reactions (ADRs) during medication regimens. By incorporating wearable physiological sensors, visual symptom analysis through camera-based systems, and multimodal machine learning models, the proposed framework

overcomes some of the current limitations of traditional pharmacovigilance systems, which are mainly dependent on retrospective reporting or individual data sources. The addition of user security management, event triggered monitoring based on medication consumption, personalized baseline establishment, and alert mechanisms also improves the proposed system's applicability for clinical use and regulatory purposes.

By virtue of its modularity, hybrid edge-cloud approach, and privacy-focused design, the framework exhibits potential for large-scale, cost-effective implementation within the hospital setting as well as the home care setting. The design analysis above underscored how lessons learned from previous research in ADR analysis, IoT healthcare systems, and clinical decision support systems had influenced the proposed approach while also justifying a need for a more proactive, patient-focused drug safety monitoring approach.

There are a number of avenues for future research. Large scale clinical validation studies are needed to evaluate the accuracy of detection, false positives, latency, and user acceptance. The sensing layer can be augmented by incorporating additional biomedical sensors such as electrocardiogram (ECG), continuous blood pressure measurement, respiratory rate measurement, and motion sensors.

In the coming versions of the mobile app, the system may include an interaction module based on voice interaction, enabling patients to enter their symptoms, confirm drug consumption, or answer automated health surveys. Speech recognition and natural language processing algorithms would further enhance multimodal data entry for ADR monitoring. Other areas of research will also include on-device inference and federated learning approaches to enhance robustness against connectivity constraints and improve data privacy. Breakthroughs in computer vision models would also allow for more accurate identification of subtle dermatological and neurological symptoms in different lighting conditions. Lastly, better integration with electronic health records and pharmacovigilance systems would enable automated reporting to health authorities and large-scale drug safety analysis. Taken together, these developments would make the proposed system a promising step towards intelligent, continuous, and personalized ADR monitoring in real-world healthcare settings.

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