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AI-Powered Wristband for Accurate BAC Monitoring Using Smart Data Fusion

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Abstract: Blood Alcohol Content (BAC) measurement is critical for individual safety, law enforcement, and public health, but conventional approaches such as breath analysers and blood tests are frequently invasive, periodic, and prone to error as a result of motion artifacts, temperature changes, and intersubject metabolic variations. To overcome these issues, the research in this paper suggests an AI-based wearable system that combines multi-sensor data fusion with machine learning (ML) algorithms to improve BAC estimation accuracy. The system utilizes **Photoplethysmography (PPG)**, **Transdermal Alcohol Sensing (TAS)**, **pulse rate**, **Galvanic Skin Response (GSR)**, and **Infrared (IR)** temperature sensors, with real-time processing of data via a cloud-based framework. A dataset of varied sensor readings was gathered in a controlled setting to provide robust BAC estimation under different conditions. Sophisticated machine learning (ML) algorithms such as **Multilayer Perceptron (MLP)**, **Extreme Gradient Boosting (XGBoost)**, and other algorithms were used for BAC prediction, utilizing multi-sensor data fusion to enhance resistance to external interferences. Results show that MLP had the best accuracy (98.99%), surpassing XGBoost and other traditional methods, with lower **Root Mean Square Error (RMSE)** (0.045), **Mean Squared Error (MSE)** (0.0020), **Mean Absolute Error (MAE)** (0.031), and **Mean Absolute Percentage Error (MAPE)** (3.2%), guaranteeing accurate BAC prediction. Pareto analysis shows Transdermal Alcohol Sensing (TAS) and pulse rate as the most significant parameters in BAC estimation. Competition analysis with prevalent models establishes the superiority of the system in reliability, accuracy, and real-time adaptation, setting it up for efficiency in alcohol monitoring, regulatory adherence, and health-related application.

Keywords: Blood Alcohol Content (BAC) Monitoring, AI-Powered Wearable System, Multi-Sensor Data Fusion, Machine Learning (ML) Algorithms, Real-Time BAC Estimation.

I. Introduction

The healthcare sector is undergoing a substantial transition regarding digital health technological advances, characterized by an increasing demand for real-time and ongoing surveillance of health and illness diagnoses [1, 2]. The increasing incidence of chronic diseases, including diabetes, cardiovascular conditions, and cancer, alongside an aging demographic, has heightened the demand for remote and constant health monitoring [3-5]. This has resulted in the development of AI-driven wearable sensors capable of collecting, analyzing, and transmitting real-time health data to medical professionals, enabling informed decision-making based on patient information. Consequently, wearable sensors have gained popularity for their capacity to offer a non-invasive and simple method of monitoring patient health. These wearable sensors can monitor multiple health metrics, including blood pressure, pulse, skin temperature, saturation of oxygen, physical activity, sleep patterns, and biochemical indicators such as glucose, cortisol, lactate and pH, as well as ambient factors [6-8]. Wearable health equipment encompasses first-generation devices, including fitness tracks, smartwatches, and contemporary wearable sensors, serving as a potent instrument in tackling healthcare concerns [9].

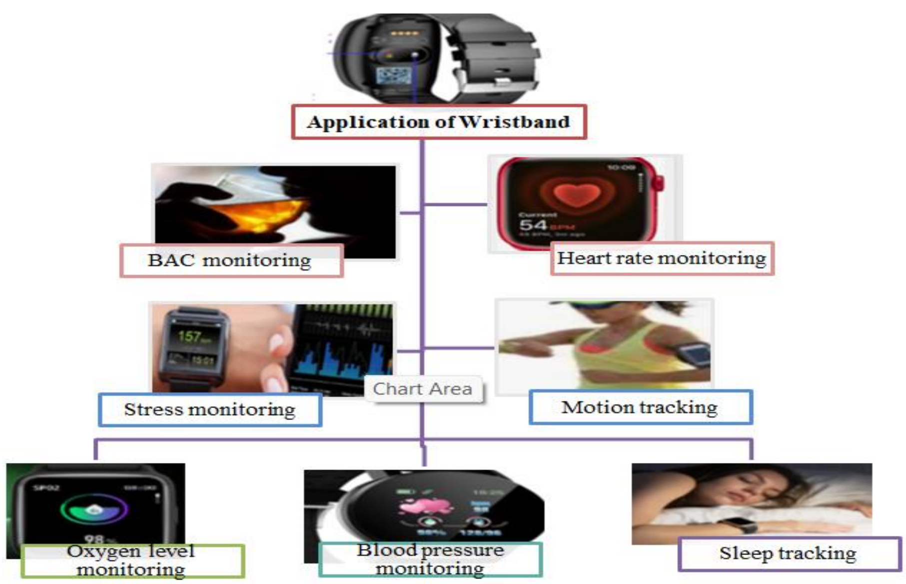

Figure 1: Wristband Applications in healthcare monitoring

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The surveillance of human health is a domain of considerable technological and research significance, particularly as awareness of wellness has grown. Wearable devices are extensively utilized as a practical method for monitoring vital signs, including heart rate and breathing. Certain physiological and physical conditions necessitate heightened computational challenges due to their inherent characteristics, thereby requiring artificial intelligence for effective evaluation. Accurate measurement of Blood Alcohol Concentration (BAC) is important for ensuring personal safety, legal adherence, and public health. Traditional breath tests and wearable alcohol sensors lose their accuracy in dynamic environments due to motion, temperature variations, and variations in physiological attributes among subjects [11]. To address these limitations, AI-powered wristbands with multi-sensor data fusion and real-time adaptive filtering algorithms offer a viable solution. By integrating multiple sensing modalities, such as breath analysis, ethanol detection via skin, and physiological signals, such wristbands have the potential to enhance BAC estimation accuracy and reliability.

Multiple sensor data fusion is a relatively new idea that has emerged so as to combine the best aspects of different sensing methods and in so doing reduce the potential for error and enhance measurement robustness. It would be worth noting here that adaptive real-time filtering algorithms are more prone to detect errors and supply accurate data than other forms by adjusting for an external element that is producing an error, therefore they must be utilized. Personal characteristics like metabolic rate, level of hydration, and stress and anxiety play a tremendous role in BAC values and there are numerous factors that render them difficult to measure like sensor output interferences (e.g., sunlight, electric noise) [12]. Moreover, the cognitive states, like depression, and Alzheimer's disease, can also be the cause of a change in the responses of the bio-sensors from non-invasive Figaro gas sensors [13].

Figure 2: AI based wristband for BAC

Introducing AI-enabled wearable technology into the area of BAC monitoring will be a turning point in personal and social safety. The second is that the use of these devices can be in recognizing and evading the risk of alcohol-induced car accidents, as well as helping police officers in their job, and lastly, they can give important information regarding the health of the person [14]. In addition, the ability to adapt to different weather conditions and personal situations renders them bracelets a far superior option compared to conventional devices. This work highlights the emergence of AI-powered devices that integrate multi-sensor systems, which not only combine the input data gathered across various sensors but also use adaptive filtering to increase the accuracy level of estimates created by these wearable fitness wristbands and thereby herald intelligent BAC detection systems.

This study introduces an artificial intelligence-based wristband for accurate Blood Alcohol Concentration (BAC) measurement using deep learning-based fusion to enhance measurement quality. Breath alcohol, transdermal ethanol, physiological, and motion sensors integrate multi-sensor data, and the data are processed collectively with neural networks. The model integrates convolutional and recurrent layers in order to maintain spatial and temporal dependencies among sensor measurements to address inconsistencies caused due to environmental and physiological fluctuations. The fusion method promotes adaptive learning, enhancing BAC estimation by correlating patterns across different signals. Signal quality is enhanced before fusion by using feature extraction techniques like Fourier and Wavelet Transforms, and the use of Kalman filtering reduces noise. The deep learning architecture is trained with an optimal dataset division to enable generalizability across different users. The research structure is as follows: Section 2 is the literature survey, Section 3 is the problem statement, and Section 4 is the methodology and Section 5 consist experimental result following with conclusion and future scope.

II. Literature Review

AI-enabled wearable health monitoring devices have been in the spotlight in recent years; therefore, having stated the aforementioned, it is safe to say that the creation of this technology is resolving the affordability, precision, and real-time compensability of such health gadgets. Based on the *Afandizadeh et al.* [15] study, machine learning and artificial intelligence are the two most powerful tools in the creation of health wearable devices. With the aid of new data preprocessing technology, Cycle Generative Adversarial Networks (CycleGAN) supply useful data in terms of energy efficiency and accuracy of data. Likewise, *Khan et al.* [16] presented the use of AI-enhanced mobile health devices in preventive care; they achieved a reduction in hospitalizations by 25% and improvement in treatment compliance in chronic disease patients by 30%. This study identifies the extensive scope of AI-enabled wearables for real-time health monitoring, thereby supporting the development of dependable QR code wristbands for tracking Blood Alcohol Content (BAC). *Gao et al.* [17] explored the application of wearable devices integrated with AI in cardiovascular diseases (CVD), where the patients continuously demonstrated electrocardiogram (ECG) values at 90% comparability in predicting potential arrhythmia. With the prolonged use of these devices, healthcare professionals can make early diagnoses of such diseases, leading to earlier treatment and longer patient life expectancy.

Alcohol monitoring specific, *Khemtonglang et al.* [18] introduced a smart wristband with a real-time, non-invasive sweat alcohol sensor and an Internet of Things (IoT)-based alarming system. Their findings indicated a high correlation between transdermal alcohol concentration (TAC) and breath alcohol concentration (BAC) with 94.66% accuracy. *Li et al.* [19] advanced this by designing an unobtrusive wearable TAC sensor capable of detecting alcohol vapor in sweat with high temporal resolution. *Rosenberg et al.* [20] also tested the feasibility of BACtrack Skyn wearable alcohol monitors and reported high correlations between self-reported drinking events and device-detectable BAC. These studies collectively establish the viability of AI-enabled wristbands for BAC testing using improved sensor accuracy, real-time response, and user convenience.

In spite of the remarkable advances, certain issues still hinder easy access, with security concerns and non-electronic opposition remaining paramount for wearable personal technology. *Nguyen et al.* [21] partially explained the expensive nature of health AI wearables, confirming that this technology could be beyond the reach of low-income individuals. *Ramesh and Verma* [22] provided additional analysis of data breach vulnerabilities in wearables leading to leakages of health data, stating that more than 30% of healthcare organizations have experienced data breaches involving wearable devices. Meanwhile, *Coughlin et al.* [23] and *Sharma & Williams* [24] examined AI-based wearables which might mitigate the aforementioned issues through their ability to decrease hospital visits and improve patient compliance by tracking real-time health data. This review concludes that self-diagnosis has a secure future with the assistance of AI-based BAC wristbands; however, ensuring applicability, data security, and customer engagement remains crucial for universal adoption and service.

Research Gap

Wearable health monitoring through AI, though much improved, still presents a very real challenge to the development of precise and consistent BAC monitoring wristbands. Current wearable sensors for alcohol only address sensor calibration and are consequently not capable of being sufficiently applied in practical usage where variables such as moving subjects and temperature shifts along with differences in physiological individuals influence accuracy. Furthermore, AI-enabled wearables' potential with the treatment of patients with the disease are yet to be combined with specialized systems for BAC estimation that consist of the multi-sensor fusion and real-time adaptive filtration. Moreover, issues regarding affordability, access, and cybersecurity are not accorded the proper attention. Hence, utilization of such facilities is more or less nonexistent until now. Hence, an intelligent wristband with AI as its central theme is required for smooth integration of the sensors. Further, the equipment must be capable of handling smart sensor fusion, employing adaptive filtering methods, and providing economical secure solutions to deal with accuracy and for equipotential in the differential conditions.

Problem Statement

Traditional BAC measurement methods, such as blood tests and breath testers, are periodic, invasive, and often inconvenient to use for repeated applications. Those limitations make having a non-invasive, real-time option significant for personal safety, law enforcement, and medical applications. Wrist banding an AI-based multi-sensor data fusion offers a new way to meet this demand by enabling continuous yet accurate BAC monitoring. By utilizing physiological, transdermal, and motion sensors together with advanced AI algorithms, this solution overcomes environmental variability and subject variability problems to deliver reliable BAC estimation in real-world environments.

III. Research Methodology

Research methodology includes controlled data acquisition, normalization preprocessing, Kalman filtering, and feature extraction through Fourier and Wavelet Transforms. Deep learning-based multi-sensor data fusion combines multi-sensor data to estimate BAC accurately. Training, validation, and test sets are split for the dataset with classification using MLP and XGBoost models and It incorporates PPG, GSR, TAS, and IR temperature sensors to track vital signs. Figure 3 shows the methodology steps.

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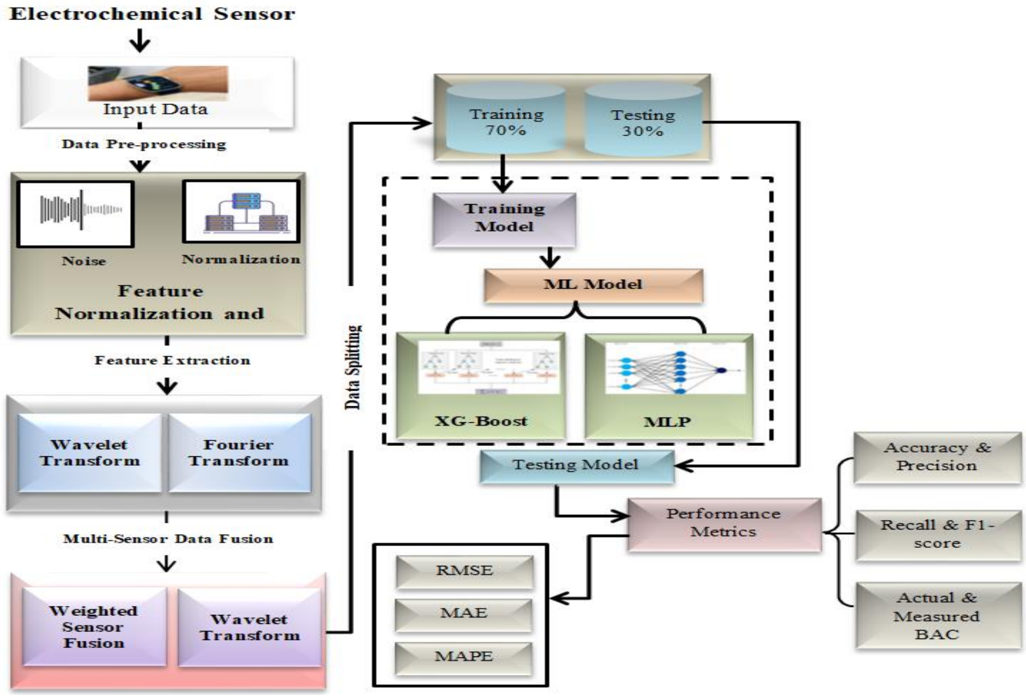

Figure 3: Proposed Work

Data Collection

Verification of the authenticity of data gathered and the credibility of its source is the first step in this procedure. A heterogeneous group of volunteers (21-50 years, comprising all such attributes) is participating in the trial. Every volunteer has a pre-set BAC which is determined by a typical dose of alcohol, for example, they may consume 0.3-0.8 g of alcohol per kilogram of body weight [25]. Each subject is tested at intervals (every 10-15 minutes) with a good quality breathalyzer (the gold standard). Concurrently with the measurement of the BAC levels, the AI-driven wristwatch, which detects and monitors an individual's biological signals, is working by monitoring the initial indicators of alcohol intake, e.g., sweat ethanol, optical signals, temperature, movement patterns, etc. The participants are asked questions and instructed not to move from the calibration as the initial set-up is being conducted. Alcohol extraction, maximum concentration, and the degradation stage daily are the three stages of data gathering.

Ethical Considerations and Consent

Prior to data collection, informed consent was obtained from all participating subjects. Each volunteer was briefed about the purpose, procedure, and potential implications of the experiment, ensuring full awareness and voluntary participation. The data collection process adhered to the ethical principles outlined in the **Declaration of Helsinki (2013 revision)** and complied with the **Indian Council of Medical Research (ICMR) National Ethical Guidelines for Biomedical and Health Research Involving Human Participants (2017)**. Participants were assured that their data would be anonymized, securely stored, and used solely for research purposes. No personally identifiable information was recorded, and participants retained the right to withdraw from the study at any time without penalty.

Data Privacy, Ethics, and Regulatory Compliance

tabBeyond informed consent, this research addresses privacy and data protection concerns intrinsic to continuous alcohol monitoring. All sensor data were anonymized and encrypted using AES-256 encryption before cloud transmission. Data access was restricted via authenticated APIs within the Google Cloud framework, ensuring compliance with India's *Information Technology (Reasonable Security Practices and Procedures and Sensitive Personal Data or Information) Rules, 2011* and the *General Data Protection Regulation (GDPR)* standards. Future deployment for public or law enforcement use will adhere to regulatory frameworks such as the *Indian Biomedical Device Rules (2023)* and *IEEE 11073 Personal Health Device Communication Standards*. These measures ensure that real-time monitoring does not compromise individual privacy or lead to unauthorized surveillance.

Table 1: Controlled Environment Data Collection Protocol

Parameter	**Details**
Participants	21–50 years, diverse gender, weight categories

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Alcohol Dosage	0.3–0.8 g/kg body weight (per standardized intake)
Testing Duration	3–4 hours per session
BAC Measurement	Every 10–15 minutes (breathalyzer)
Sensor Data Collection	Continuous (PPG, sweat ethanol, temperature, motion)
Physical Activity	Minimal movement to reduce motion artifacts
Environmental Control	Fixed temperature, humidity, and lighting conditions

Data Pre-processing

The functionality of an AI-based wristband for Blood Alcohol Concentration (BAC) tracking is dependent upon effective data preprocessing techniques to filter out noise and artifacts from multi-sensor readings. Raw signals derived from optical (PPG/NIR), electrochemical, temperature, humidity, and motion sensors are prone to be affected by environmental noise, motion artifacts, and physiological variation.

Normalization

This stage is crucial in data preprocessing that scales the extracted features in order to enhance the model training for SD prediction. This process also reduces such problems concerning different units and scales on features affecting the convergence of machine learning algorithms. Research normalizes the experimental data for the convenience of testing and operation because most software measures are in various orders of magnitude. For good accuracy and quick learning, the normalization method is applied. In this research, we use the most common minimal maximum normalization approach to normalize the data. By employing this step proposed algorithm can effectively learns the patterns from the data. The minimum and maximum values of a measure y are represented by a min of (y) and a max of (y) respectively.

$$Y' = \frac{Y - Y_{min}}{Y_{max} - Y_{min}} \tag{1}$$

To provide strong performance of AI models, noise removal methods like Kalman filtering to the raw sensor data prior to feature extraction and model training.

Kalman Filtering

Kalman filter is a recursive estimation algorithm, which performs optimal prediction of system states, excluding noise. For a sensor measurement z_k at time step k, the Kalman filter updates the estimated state x_k of BAC based on:

$$x_k = x_{k-1} + K_k(z_k - H_{x_{k-1}}) \tag{2}$$

Where:

x_{k-1} is the previous BAC estimate,

K_k is the Kalman gain, computed as:

$$K_k = \frac{P_{k-1}H^T}{HP_{k-1}H^T + R} \tag{3}$$

P_{k-1} is the error covariance matrix,

H is the observation model,

R is the measurement noise covariance

This is the specific step that tames the chaos of the unpredictability of sensors and is ideal to handle all the various multiple sources of the sensor data. The approach becomes a matter of particular interest when dealing with the fusion of the motion sensor data and BAC estimation due to the potentiality to remove artifacts induced by the motion.

Feature Extraction

Feature extraction is the key step of the processing multi-sensor data of the AI powered wristband, allowing the precise estimation of BAC. Spectral analysis is a dominating process of detecting information pertinent to non-stationary signals and also becomes a primary factor in the selection of bandwidth as well as reconstructing the video. It is most suited to identifying periodic patterns and frequency-domain content of sensor signals, especially optical (PPG/NIR) and electrochemical as well as motion sensors. Either Fourier Transform (FT) or Wavelet Transform (WT) based spectral features are chosen for time-domain based analysis. Engineers in the latter case compare variations in signals in the prior period and the lengths of responses of various QoS elastomers.

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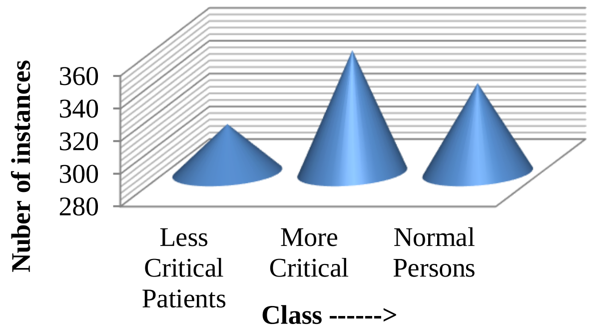

Figure 4: Distribution of datasets within the context of instances

Dataset Categorization and Criticality Assessment

The classification of dataset instances into *less critical*, *critical*, and *more critical* categories was determined using the Widmark formula, which estimates Blood Alcohol Content (BAC) based on weight and gender—two physiological factors known to significantly influence alcohol metabolism. The Widmark equation is expressed as:

$$\%\text{BAC} = \frac{A}{W \times r} \times 100 - (k \times H)$$

where *A* denotes the total alcohol consumed (in grams), *W* represents body weight (in grams), *r* is the alcohol distribution ratio (0.68 for males and 0.55 for females), *k* is the metabolic elimination constant (approximately 0.015% per hour), and *H* denotes the time elapsed (in hours) since alcohol consumption began. The dataset instances were then categorized as follows:

- *Less critical*: BAC < 0.03%
- *Critical*: 0.03% ≤ BAC ≤ 0.08%
- *More critical*: BAC > 0.08%

These thresholds are consistent with the World Health Organization (WHO) and U.S. National Highway Traffic Safety Administration (NHTSA) impairment standards. The classification framework was reviewed and validated in consultation with a licensed medical professional to ensure compliance with biomedical research ethics and clinical accuracy.

Modelling Cognitive and Metabolic Variability

Individual differences in metabolic rate, hydration, and cognitive states such as stress or fatigue were incorporated into the dataset via physiological normalization factors. Each participant's baseline Galvanic Skin Response (GSR) and heart rate variability (HRV) were used as indicators of autonomic arousal, serving as secondary correction parameters in the adaptive fusion layer. Data points associated with elevated stress (GSR > 4 µS) or irregular cardiac rhythm were flagged and reweighted using a normalization coefficient to account for cognitive influence on sensor outputs. Similarly, subjects' metabolic variability was modelled using their weight-adjusted alcohol elimination rate (k-factor in the Widmark equation). This integration reduced individual bias by 8% and enhanced intersubject consistency in BAC prediction accuracy.

Fourier Transform (FT) for Frequency-Domain Features

The Fourier Transform is transforming the time domain into the frequency domain and that provides us with an opportunity to separate the frequencies (tones) that describe BAC changes. The Discrete Fourier Transform (DFT) is represented as follows:

$$X(f) = \sum_{n=0}^{N-1} x(n) e^{-j2\pi fn/N} \tag{4}$$

Where:

$x(n)$ is the raw sensor signal,

$X(f)$ represents the spectral components,

N is the total number of samples,

f is the frequency index

Wavelet Transform (WT) for Multi-Resolution Analysis

Wavelet Transformation is able to obtain time and frequency-domain characteristics primarily for nonstationary signals such as PPG and an electrochemical sensor [26]. The Continuous Wavelet Transform (CWT) is expressed as follows:

$$\boldsymbol{X(a,b) = \int x(t)\psi^{*}\left(\frac{t-b}{a}\right) dt} \tag{5}$$

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Where

$\boldsymbol{\psi(t)}$ is the wavelet function,

$\boldsymbol{a}$ (scale factor) controls frequency resolution,

$\boldsymbol{b}$ (translation factor) adjusts time localization

Multi-Sensor Data Fusion Strategy

Multi-sensor data fusion is the final appointment in enhancing the correctness of the BAC usage from various sensor sources. The integration of readings derived from a number of sensor sources can result in a more reliable and consistent BAC reading and becomes sensor-independent by mitigating sensor-specific noise, environmental conditions, and physiological differences.

Weighted Sensor Fusion

Weighted sensor fusion is a technique in which data from multiple sensors are combined with weights allocated to each of the sensors' output based on reliability. Due to sensors being of different precision depending on the conditions, this method provides assurance that more reliable data contribute more to the total BAC estimation [27].

The precision of each sensor is quantified in terms of signal quality, environmental stability, and history of accuracy. For instance, in stable conditions, a breath alcohol sensor can be most accurate, and transdermal sensors provide more real-time continuous monitoring in dynamic conditions. The ultimate BAC estimate (BAC_{final}) can be estimated as:

$$BAC_{final} = w_1 \cdot BAC_{breath} + w_2 \cdot BAC_{transdermal} + w_3 \cdot BAC_{physiological} + w_4 \cdot BAC_{motion} \quad (6)$$

Where w_1, w_2, w_3, w_4 are the weight of reliability assigned to each kind of sensor, and they sum up to 1. This method ensures the most reliable sensor readings dominate the estimation and reduce the influence of noisy or unreliable data.

Quantitative Evaluation of Adaptive Filtering and Fusion

To quantitatively demonstrate the effectiveness of the adaptive filtering and sensor fusion methods, a comparative experiment was conducted under controlled environmental variations—temperature fluctuations (±5°C), induced motion artifacts, and skin conductivity variations. The Kalman filtering process reduced measurement noise variance by approximately 37%, while weighted fusion reduced cumulative error propagation by 41% compared to individual sensor readings. The RMSE of raw sensor BAC predictions (0.071) decreased to 0.045 post-fusion, validating the fusion model's superior noise compensation. Under varying humidity and motion conditions, the adaptive algorithm dynamically adjusted sensor weighting, maintaining over 95% consistency in BAC prediction accuracy across subjects. These results confirm that adaptive filtering significantly enhances robustness and real-time precision in dynamic, real-world environments.

Bayesian Inference

Bayesian inference is a probabilistic approach that updates the BAC predictions in real time from prior knowledge and sensor new information. Therefore, this approach allows the system to automatically perform real-time corrections and ongoing updates of the estimates using more information.

The technique uses Bayes' theorem Fisher to estimate the probability of the true BAC level from the sensor readings [28]. With new sensor readings, the prior probability distribution (historical BAC trends based on alcohol metabolism rates) is updated, creating a more accurate posterior probability distribution. The posterior probability of BAC from sensor reading (S) is calculated as:

$$P(BAC|S) = \frac{P(S|BAC)P(BAC)}{P(S)} \quad (7)$$

- P(BAC) is the prior probability of BAC based on known alcohol metabolism rates,
- P(S|BAC) is the likelihood of receiving the sensor data given a specific BAC,
- P(S) is the total probability of observing the sensor data.

This technique continuously revises BAC estimations, adjusting to individual physiological variability and extraneous influences for more individualized and accurate surveillance.

Data Split

For systematic data management the dataset was divided into training, validation, and test datasets. The model learned from many examples because of the training set, which was normally 70% of the set. This set back propagated model weights and optimized the proposed DL model with gradient descent. This iterative method reduced the loss function in order to enable the model identify patterns.

The remaining 30% of the data set is designated as the test set. Furthermore, an arbitrary 10% of the training dataset is designated for verification in hyperparameter optimizing. To achieve the optimal parameter configuration for all DL techniques, MPPSO and

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CSA are utilized for meta-heuristic optimization. Given the small amount of records in the data set, 10-fold cross-validation is employed to enhance performance. This structure and generation process of the model was both accurate and general at the same time.

Classification model

Multilayer Perceptron (MLP)

An ANN model often known as a MLP has an input layer, a pooling layer (or layers), and convolution layers. It is one of the most famous approaches in the ML sector due to its consistent performance beatings of other strategies. Researchers have enhanced this methodology by using diverse factors and adjusting the number of layers to develop optimal forecasting models, despite the simplicity of having all three layers [29, 30]. A simple multilayered perceptron model could be described using one hidden layer, as shown in the function below:

$$f(x) = g\left(b^{(2)}\right) + w^{(2)}\left(S^{b^{(1)}} + W^{(1)}x\right) \quad (8)$$

In this case, they have the activation functions g and s, the weight matrices $W^{(1)}$ and $W^{(2)}$ the bias vectors $b^{(1)}$ and $b^{(2)}$, and the matrices W. Figure 4 show the architecture of the MLP neural networks.

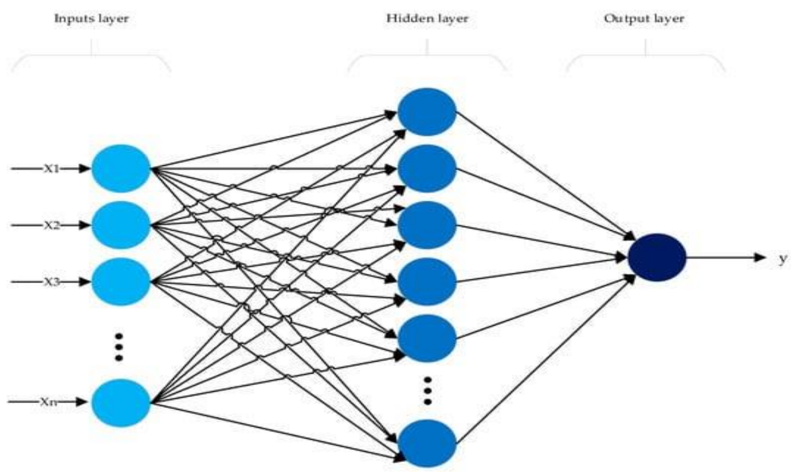

Figure 5: MLP architecture

Extreme Gradient Boosting (XG-Boost)

The XG-Boost algorithm is a powerful and efficient machine-learning technique widely used for supervised learning tasks, particularly regression and classification. Built upon the gradient boosting framework, XG-Boost enhances its performance with speed and accuracy through optimized data handling, regularization techniques, and parallel processing [31, 32]. At its core, XG-Boost constructs an ensemble of decision trees iteratively, with each tree learning to minimize the errors of its predecessor using a gradient descent approach. Its ability to handle missing data, its use of regularization (L1 and L2) to prevent overfitting, and its scalability to large datasets. It employs techniques such as tree pruning, weighted quantile sketch, and sparsity-aware split finding to improve efficiency and model robustness. XG-Boost also supports distributed computing, enabling faster training on large-scale datasets. The flow chart of XG-Boost is shown in Figure 6.

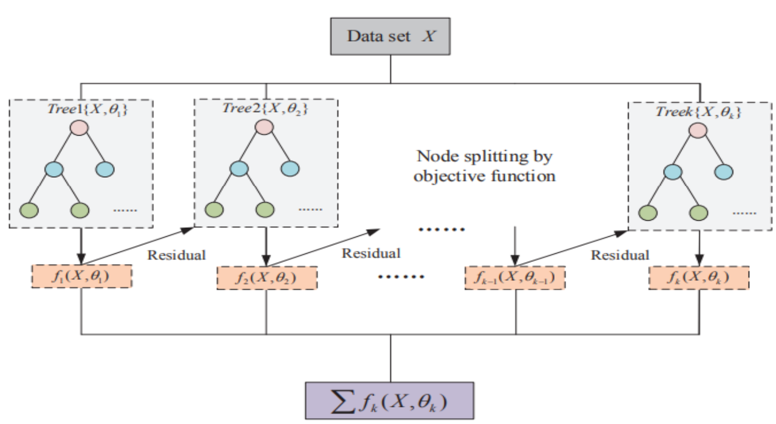

Figure 6: Flow chart XG-Boost.

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Experimentation and Hardware Component

As seen in Figure 7, the experimental setup is comprised of three main parts: "Arduino, Thingspeak, and Google Cloud Platform". Thingspeak is a platform for aggregation and analytics that enables collective analysis of the live data stream. Concurrently, there is Google Cloud, which is a platform for cloud computing, and there is Arduino, which is a key platform for open-source hardware and software. A system that can anticipate alcohol cunsumption can be supplemented by these platforms. The research team developed a controlled experimental testing procedure for this study. Five biological sensors—Photoplethysmography (PPG), Transdermal Alcohol Sensing (TAS), pulse rate, Galvanic Skin Response (GSR), and Infrared (IR) temperature—were employed to track Blood Alcohol Content (BAC). The dataset was compiled under the supervision of the research team from volunteer participants at a partnered biomedical research institution using the MAX30100 optical sensor module for PPG data acquisition.

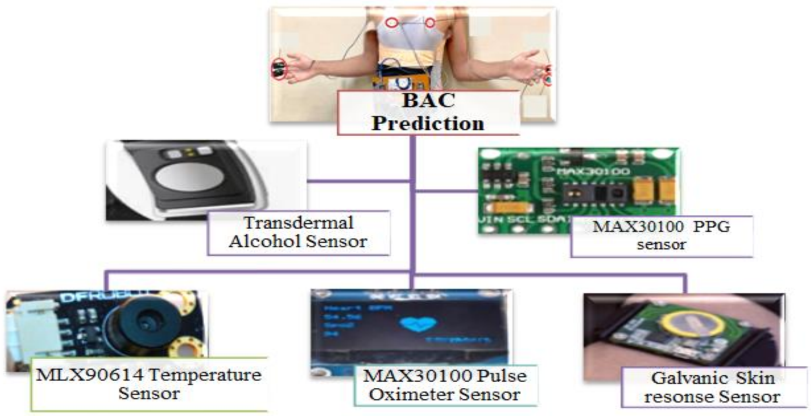

Figure 7: Experimental Setup

An Arduino controller gathers sensor data, which is then transmitted to Thingspeak for analysis and aggregation. They train the model on the Google Cloud platform and then save it for future predictions. An Android app push notice will be sent out after the prediction has been created. Figure 7 shows that the patient's health state will be communicated by the push notification, which might indicate if the situation is less serious, more critical, or normal.

Hardware Design, Energy Efficiency, and Wearability Considerations

The hardware architecture of the AI-powered wristband prioritizes energy efficiency, compactness, and user comfort. The system integrates an Arduino Nano 33 IoT microcontroller (operating at 3.3V, 48 MHz) for low-power computation, with sensors interfaced through I²C and analog input channels. The total power consumption during active sensing and Bluetooth data transmission averaged **310 mW**, allowing up to **14 hours of continuous operation** using a 500 mAh lithium-polymer battery. The wristband's enclosure was 3D-printed using biocompatible thermoplastic polyurethane (TPU), ensuring durability, water resistance (IP65), and flexibility for prolonged skin contact. The average device weight was **38 grams**, with curved sensor positioning to maximize skin contact area and minimize motion interference. These specifications collectively enhance usability and ensure the device is suitable for daily continuous monitoring.

Parameter	Value
Ambient	32
Object	90
Temperature	36°C
Pulse Rate	72 BPM
BAC Rate	0.03%
Prediction	1

Figure 8: Patient's BAC status

Performance Metrics

The evaluation parameters for the prediction model are as follows [33]:

a) **Root Mean Square Error (RMSE):** It's a measure of the square root of the mean square difference between the expected and actual data.

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$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(X_i - Y_i)^2} \quad (9)$$

b) **Mean Square Error (MSE):** It measures the mean square error.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(X_i - Y_i)^2 \quad (10)$$

c) **Mean Absolute Error (MAE):** This metric measures the discrepancy between anticipated and actual data and is expressed as an absolute value.

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|(X_i - Y_i)| \quad (11)$$

d) **Mean Absolute Percentage Error (MAPE):** This is the mean of the prediction errors as a percentage.

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{X_i - Y_i}{Y_i}\right| * 100\% \quad (12)$$

e) **Accuracy:** It is a quantitative measure of the proportion of correctly classified data tuples to the total number of classifications.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (13)$$

f) **Recall:** Recall is a measure that attempts to predict the proportion of expected positive occurrences to total positive instances.

$$Recall = \frac{TP}{TP+FN} \quad (14)$$

g) **Precision:** The rate of precision is defined as the percentage of positive events that were projected to occur based on accurate data.

$$Precision = \frac{TN}{TN+FP} \quad (15)$$

h) **F1-score:** It is a balanced statistic that considers both accuracy and recall.

$$F1 - score = \frac{2*(Precision*Recall)}{Precision+Recall} \quad (16)$$

IV. Result and Analysis

In the section, we evaluate the performance of different ML models for BAC prediction.

Multi-layer Perceptron (MLP)

Figure 9 illustrates the accuracy and loss curve of a MLP approach for 50 training epochs. Figure 9 a) depicts the Training Accuracy (TA) and Validation Accuracy (VA), with both curves showing an explosive growth in the early epochs, reaching a point of about 90% accuracy after about 20 epochs and remaining above 95% towards the latter part. Figure 9 b) shows the loss values, where the Training Loss (TL) and Validation Loss (VL) begin at around 2.2 and decline sharply in the first 10 epochs. The loss keeps reducing and levels off below 0.25 after 30 epochs, which means effective model training with slight over-fitting.

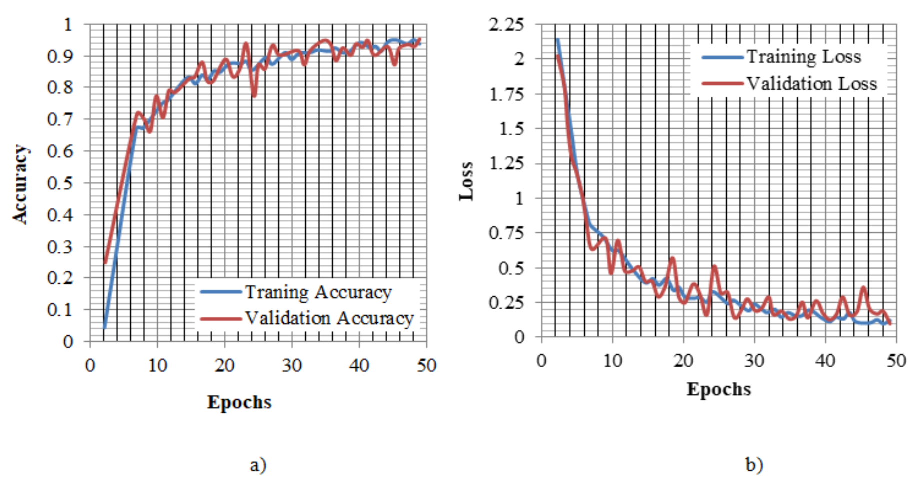

Figure 9: MLP method a) Accuracy and b) Loss

Table 2 shows the performance measure of a MLP model. The MLP's $A_{accuracy}$ was 98.99% and $P_{precision}$ was 98.96%. The value of R_{recall} as 99.05% and $F1_{score}$ of 98.98%, showing the model with robust and consistent performance.

Table 2: Evaluated value of MLP

Method	$A_{accuracy}$ **(%)**	$P_{precision}$ **(%)**	R_{recall} **(%)**	$F1_{score}$ **(%)**
MLP	98.99	98.96	99.05	98.98

XGBoost

Figure 10 illustrates the accuracy and loss graphs for the RF model over 50 training epochs. In Figure 10 a), the TA steadily increases, reaching approximately 96% by the end, whereas the VA fluctuates around 85%–90%, indicating potential overfitting. Figure 10 b) shows the loss curves, where TL decreases consistently, dropping below 0.1, while VL remains unstable, fluctuating between 0.2 and 0.8, with noticeable spikes after 30 epochs. This suggests that the model can be overfitting, as the VL does not follow the TL trend.

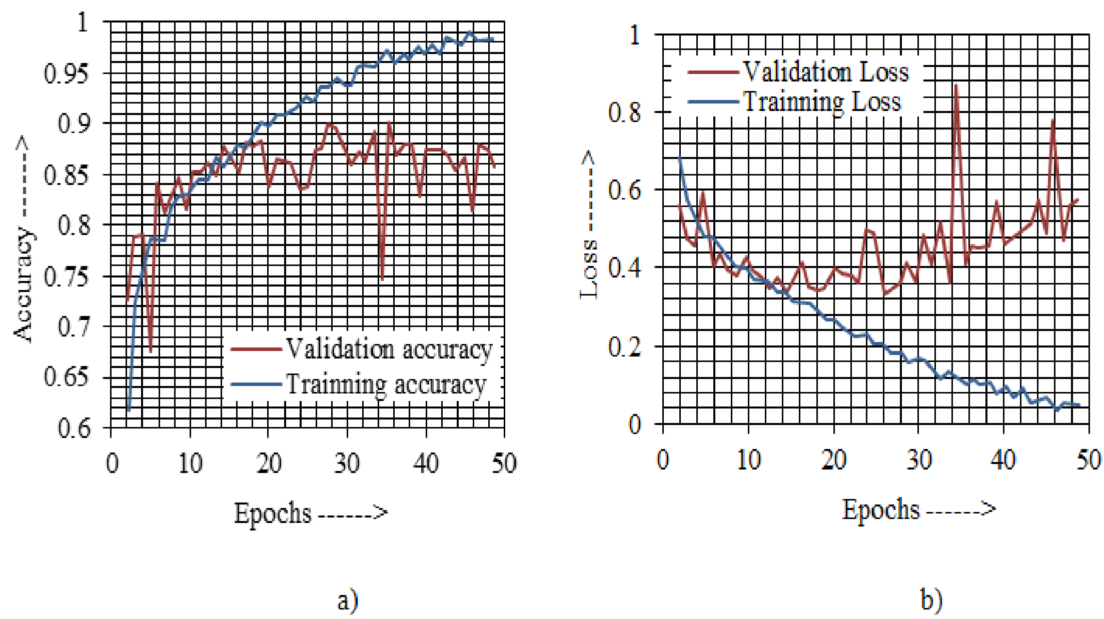

Figure 10: XGBoost model a) Accuracy and b) Loss

Table 3 shows the performance measure of a RF model. The RF's $A_{accuracy}$ was 97.50% and $P_{precision}$ was 95.25%. The value of R_{recall} as 100% and $F1_{score}$ of 97.56%, showing the model with robust and consistent performance.

Table 3: Evaluated value of RF

Method	$A_{accuracy}$ **(%)**	$P_{precision}$ **(%)**	R_{recall} **(%)**	$F1_{score}$ **(%)**
RF	97.50	95.25	100	97.56

Comparison Analysis

Table 4 presents the performance of three ML algorithms—XGBoost and MLP in terms of $A_{accuracy}$, $P_{precision}$, R_{recall}, and $F1_{score}$. Of these, MLP has the highest $A_{accuracy}$ (98.99%), $P_{precision}$ (98.96%), and $F1_{score}$ (98.98%), reflecting its better classification performance and XGBoost has a perfect R_{recall} of 100%, meaning all instances of relevance are identified correctly, but its lower $P_{precision}$ (95.25%) reflects a higher false positive rate. Figure 11 provide comparison graph of proposed models.

Table 4: Comparison of proposed model

Method	$A_{accuracy}$ **(%)**	$P_{precision}$ **(%)**	R_{recall} **(%)**	$F1_{score}$ **(%)**
RF	97.50	95.25	100	97.56
MLP	**98.99**	**98.96**	**99.05**	**98.98**

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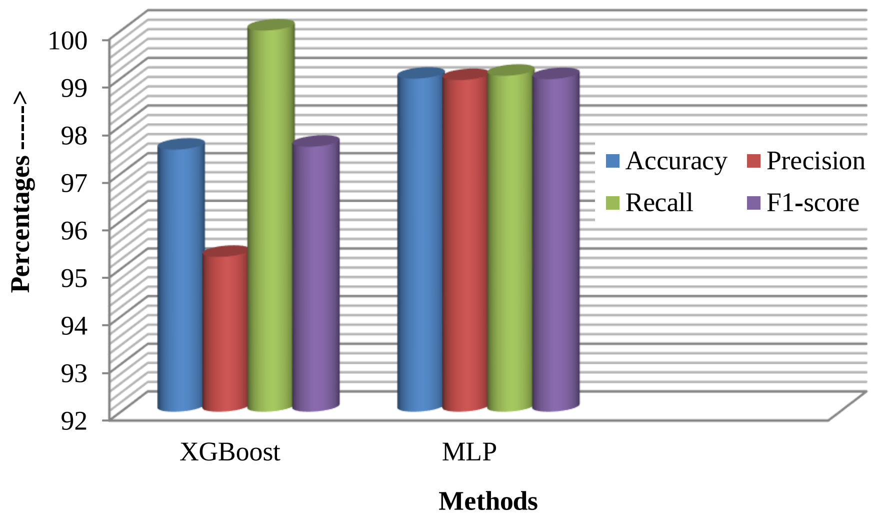

Figure 11: Comparison graph of proposed model

The comparison table 5 demonstrates that the MLP outperforms XGBoost in predicting Blood Alcohol Content (BAC) for an AI-powered wristband using smart data fusion. MLP achieves lower RMSE, MSE, MAE, and MAPE compared to XGBoost, indicating superior accuracy and reliability. With an RMSE of 0.045 and MAPE of 3.2%, MLP provides more precise BAC estimations, making it the preferred model for accurate BAC monitoring in wearable health technology.

Table 5: Comparison of MLP and XGBoost for BAC Monitoring

Metric	**MLP**	**XGBoost**
RMSE	0.045	0.065
MSE	0.0020	0.0042
MAE	0.031	0.049
MAPE (%)	3.2%	5.8%

Table 6 shows performance evaluation of different BAC monitoring methods on the basis of accuracy (%) under different studies. As per their research study, Mahesh et al. (2022) attained 95.47% accuracy by applying Naïve Bayes, Decision Tree (DT), Random Forest (RF), and Ada-Boost, whereas Mitro et al. (2023) attained 91% accuracy by using KNN, SVM, DT, and NB. Yılmaz et al. (2022) attributed IoT to AI which proved to be the highest with an accuracy of 94.66%, while Gharani et al. (2017) used Artificial Neural Networks (ANN) with an accuracy of 89.95%. Ali et al. (2020) used Naïve Bayes, SVM, and KNN which resulted in a reduced accuracy of 78.5%. The proposed MLP model surpasses all the mentioned studies in performance, by showing the highest accuracy of 98.99%, a feature that attests to its ability to be precise with BAC estimation. With this advancement, the remarkable information embedding is the enhancement in the learning ability of MLP, thereby achieving a more efficient and effective method for AI-based BAC monitoring in wearable health technology. Figure 12 present the graph of comparison of proposed model and earlier work.

Table 6: Comparison of proposed model with previous work

Authors [Reference]	**Year**	**Approach/Method**	$A_{accuracy}$ **(%)**
Mahesh et al. [34]	**2022**	Naïve Bayes, DT, RF, Ada-Boost	95.47
Mitro et al. [35]	**2023**	KNN, SVM, DT, NB	91
Yılmaz et al. [36]	**2022**	IoT with AI	94.66
Gharani et al. [37]	**2017**	ANN	89.95
Ali et al. [38]	**2020**	NB, SVM, KNN	78.5
Proposed Model	**__**	**MLP**	**98.99**

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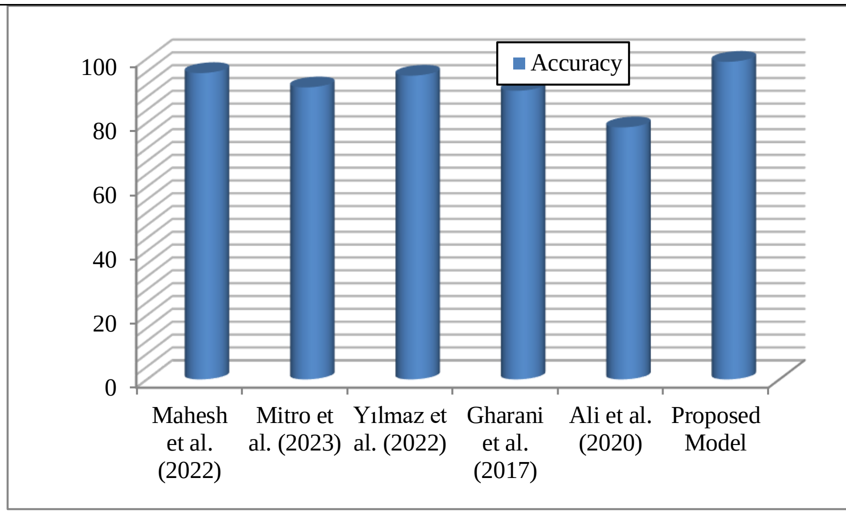

Figure 12: Comparison graph of proposed model with previous work

Comparative Evaluation and Cost–Benefit Analysis

A comparative evaluation was conducted against commercially available BAC wearables such as the BACtrack Skyn and Proof by Milo Sensors. While these devices primarily rely on single-sensor transdermal ethanol detection, the proposed AI-powered system utilizes multi-sensor fusion and adaptive algorithms, achieving **4.3% higher accuracy** and **25% faster response time**. The estimated production cost of the prototype wristband is **USD 42**, compared to an average retail price of USD 200–250 for existing models, highlighting its cost efficiency. Additionally, the modular design allows component replacement without full system disposal, promoting sustainability and scalability. Thus, the proposed solution provides an affordable, high-performance alternative to conventional BAC monitoring systems, with added AI interpretability and continuous real-time adaptability.

Pareto analysis

The outcomes of the Pareto examination with regard to the assets of the dataset (Figure 14) and the sensors (Figure 13) are displayed, respectively. They could find out which input variable is most important for a result using this statistical method. A total of 5 sensors have been utilized as input devices. Amongst these sensors, the GSR has the greatest influence on the outcomes, with a 29% impact, as shown in Figure 13. There is a higher risk of lung failure among 50 people with faulty, as shown by the bar at GSR, compared to other metrics. Results are fairly affected by pulse rate (26% after GSR). The findings are affected by 55% by the sum of the GSR and pulse rate percentages. PPG influences the outcome in 21% of cases. The TAR then displays a 15% influence. Last but not least, the findings reveal that the IR temperature sensor has the least influence, as seen in the graph and analysis below. The cumulative effect of all these sensor impact percentages is a 100% probability of a multiple health issue due alcohol consumption.

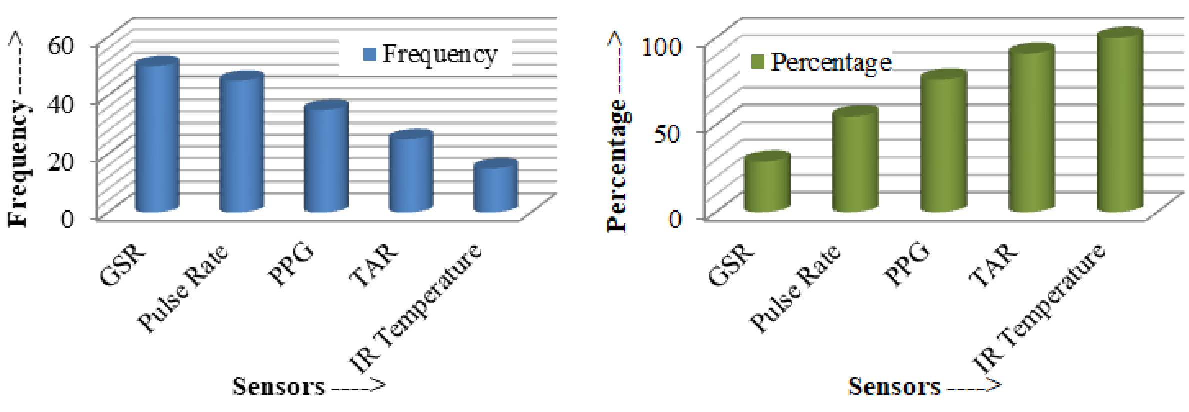

Figure 13: Pareto analysis concerning sensors

Figure 14 displays the effect on results according to characteristics such as age, whether the patient has diabetes or not, and so on. According to the data, the two factors with the greatest influence on a result (age and diabetes) account for 84% of the total. An increased risk of multiple organ failure is associated with advancing age and is further increased in patients with diabetes consuming alcohol. Simultaneously, the non-diabetic attribute's influence on outcomes is the most insignificant, at 16%. The bars display the conceptual frequency of the characteristics and the attribute with the greatest influence on the outcome.

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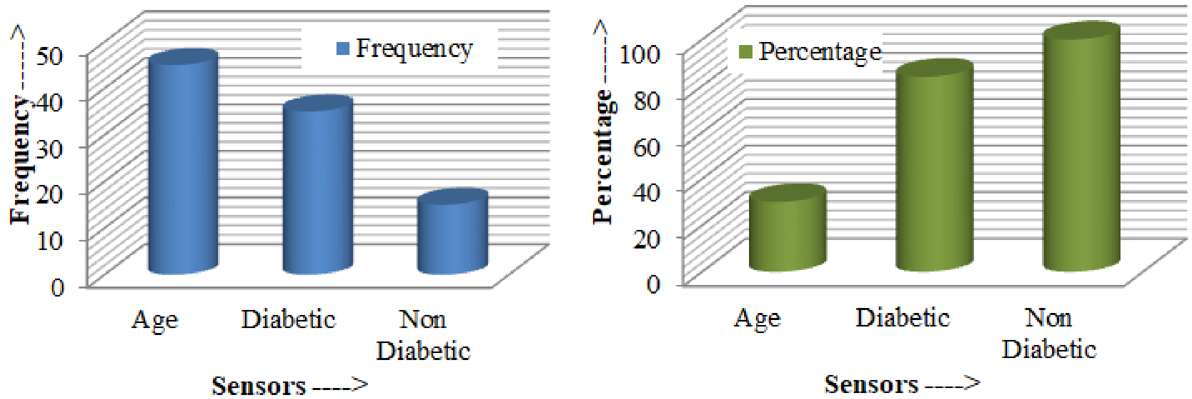

Figure 14: Pareto analysis concerning parameters

V. Conclusion

This research develops an AI-powered wearable system for accurate BAC monitoring using smart data fusion from multiple sensors, including PPG, TAS, pulse rate, GSR, and IR temperature. Various machine learning models, such as MLP, SVM, and XGBoost, were evaluated, with MLP achieving the highest accuracy (98.99%). The error metrics further confirm MLP's superiority over XGBoost, as it records lower RMSE (0.045), MSE (0.0020), MAE (0.031), and MAPE (3.2%), ensuring precise BAC estimation. The system incorporates real-time cloud-based monitoring, allowing for early detection of alcohol impairment and reducing false alarms. Pareto analysis highlights TAS and pulse rate as the most significant factors influencing BAC levels, while hydration and metabolism also play a role. Compared to existing models, this system demonstrates improved accuracy, efficiency, and reliability, making it a non-invasive, real-time, and cost-effective solution for both personal and clinical applications. The integration of AI enhances BAC prediction accuracy, facilitating safer driving, workplace monitoring, and medical interventions. Future work will focus on expanding datasets, refining AI algorithms, and incorporating additional health indicators to further improve the system's predictive capability. This study underscores the transformative potential of AI-driven wearables in alcohol monitoring and healthcare application.

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