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SmartBio: An AI-Enabled Smart Medical Device for Early Cancer Detection using Variational Autoencoders and Multimodal Sensor Integration

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ABSTRACT

This research explores the capability of a generative AI model called Variational Autoencoder (VAE), leveraging device sensors such as breath acetone and sweat biomarkers to identify life-threatening diseases, such as cancer, diabetes, and heart disease at earlier stages and help address metabolic issues. These sensors are intended to be integrated into smart devices such as wearable fitness trackers or smartwatches. The sweat biomarker sensor collects data from perspiration, including lactate, glucose, cortisol, and sodium levels. The breath acetone sensor measures the concentration of acetone in exhaled breath a byproduct of fat metabolism that reflects metabolic state. Both sensors can help assess mitochondrial quality, a core parameter for predicting diseases like cancer, diabetes, and cardiovascular disorders. The work demonstrates the efficacy of the system, achieving a training accuracy of 92%, testing accuracy of 89%, and an anomaly detection rate of 90%, with a low false positive rate of 5%. A reconstruction error threshold of 0.1 was empirically determined to differentiate between normal and abnormal patterns. The system's architecture built on Azure cloud and edge infrastructure supports secure data storage, low-latency inference, and personalized health recommendations via mobile interfaces. Overall, SmartBio offers a proactive and scalable solution for personalized metabolic health monitoring, paving the way for early intervention and lifestyle-driven disease prevention.

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1. INTRODUCTION

Chronic lifestyle diseases such as cancer, diabetes, and cardiovascular disorders remain the leading causes of mortality globally. According to the 2023 National Diabetes Statistics Report, an estimated 38.4 million individuals in the United States—approximately 11.6% of the population—are living with diabetes. Among adults aged 18 years and older, this prevalence rises to 14.7%. Similarly, cancer continues to pose a major public health challenge. As per the United States Cancer Statistics (USCS), 1,777,566 new cancer cases were reported in 2021, with 608,366 deaths occurring in 2022 alone. Despite national initiatives such as the 1971 National Cancer Act and the 2016 Cancer Moonshot, mortality rates remain alarmingly high [1]-[3].

In the context of cardiovascular disease, the statistics are equally concerning. The U.S. Centers for Disease Control and Prevention (CDC) report that heart disease is the leading cause of death, with one individual succumbing every 33 seconds. In 2022, the death toll from heart-related complications reached 702,880, and the economic burden

of cardiovascular care amounted to $252.2 billion during 2019–2020. These figures underscore the urgent need for effective, scalable preventive measures to reduce disease incidence and mortality through early detection and behavioural modification [4].

A growing body of evidence identifies poor dietary habits and disrupted metabolic processes as root causes of many chronic conditions. Key culprits include excessive consumption of refined sugars, simple carbohydrates, and trans fats—all of which adversely affect mitochondrial function. The mitochondrion, often described as the cell's "powerhouse," plays a central role in energy metabolism. Impaired mitochondrial health is strongly associated with obesity, insulin resistance, cancer progression, and cardiovascular dysfunction. Given this backdrop, it becomes imperative to monitor mitochondrial health continuously and non-invasively. Traditional diagnostic techniques often fail to detect metabolic degradation at an early stage, when intervention is most effective [5]-[6].

This paper introduces SmartBio, a wearable device that integrates real-time biosensing with AI-driven analytics to address this gap. By analyzing exhaled breath acetone and sweat biomarkers and applying VAEs for anomaly detection in the latent metabolic space, the system enables early identification of metabolic disruptions. The aim is to empower individuals to proactively modify their lifestyle based on scientifically grounded insights, thereby reducing the incidence and impact of non-communicable diseases. This research contributes a novel paradigm in preventive healthcare—where technology not only tracks but also interprets physiological signals to deliver actionable, personalized guidance. The remainder of the paper elaborates on sensor technologies, the VAE architecture, latent space mapping, and system integration for real-time deployment. A schematic representation of the proposed system is shown in Figure 1.

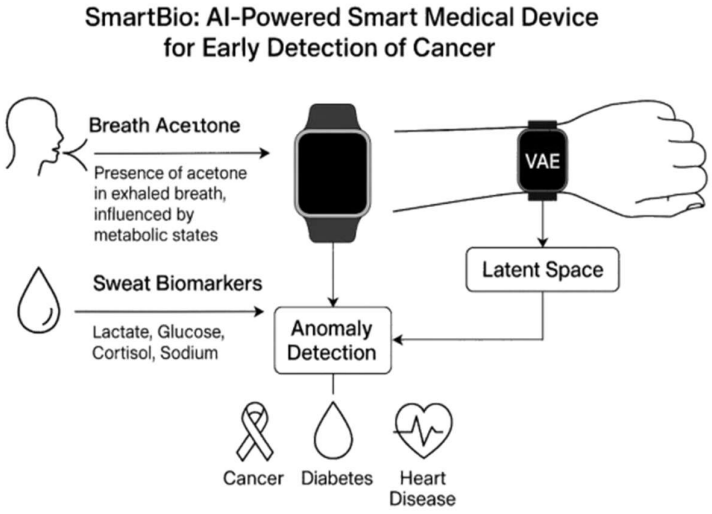

Figure1. Framework of proposed system.

2. RELATED WORK

In recent years, there has been growing momentum in leveraging biosensing technologies and artificial intelligence for proactive health monitoring and early disease detection [7]-[8]. Traditional preventive healthcare systems rely heavily on periodic annual checkups, which often miss the subtle, early-stage metabolic imbalances that precede chronic conditions such as cancer, diabetes, and cardiovascular diseases. The proposed SmartBio system seeks to transcend this limitation by enabling continuous, real-time physiological monitoring through the integration of sweat and breath sensors with advanced generative AI models—particularly VAEs—deployed using the computational infrastructure of the Microsoft Azure cloud platform [9].

Existing studies in nutritional and metabolic science have underscored the critical role of mitochondrial function in the pathogenesis of lifestyle diseases. Colbert [10], in *Beyond Keto*, notes that cancer cells exhibit a high dependency on glucose for proliferation and survival. By contrast, a ketogenic (fat-based) metabolic state deprives cancer cells of their primary energy source, thereby inhibiting their growth. This biological insight offers a foundation for therapeutic strategies that prioritize mitochondrial health and regulate glucose intake. Similarly, Joseph [11], in *Fat for Fuel*, articulates a compelling argument that mitochondrial dysfunction is a primary cause—not a consequence—of cancer. He explains that healthy mitochondria facilitate efficient oxidative phosphorylation, whereas cancerous cells shift to anaerobic glycolysis (the Warburg effect), bypassing the mitochondrial energy

pathway. This metabolic switch is not only inefficient but also conducive to rapid tumour growth. Accordingly, Mercola advocates for a fat-adaptive metabolic state through low-carbohydrate, high-fat diets to enhance mitochondrial resilience and reduce cancer risk.

The correlation between glucose-driven metabolism, insulin resistance, and mitochondrial degradation forms the basis for understanding the onset of diabetes and its downstream effects on cardiovascular health. As insulin resistance intensifies, glucose utilization becomes impaired, resulting in a compensatory shift that burdens the mitochondria, leading to systemic inflammation and increased oxidative stress—precursors to heart disease. By promoting a ketogenic metabolic state, in which mitochondria utilize ketone bodies rather than glucose, overall mitochondrial quality and energy output improve, reducing the risk of metabolic disease progression.

However, despite the scientific understanding of dietary impacts on mitochondrial health, behavioural adherence to healthy lifestyle changes remains a major challenge. Saraf and Saraf [12], in *The Satvic Revolution*, argue that processed food industries exploit human psychological vulnerabilities by engineering highly palatable, addictive foods laden with sugar and refined carbohydrates. These foods override natural satiety mechanisms and foster habitual consumption patterns detrimental to long-term health. As a result, even motivated individuals tend to relapse into unhealthy habits shortly after gaining awareness—whether through health screenings, social exposure, or personal experiences. To address this motivational gap, James Clear's [13] behavioural science principles from *Atomic Habits* are particularly relevant. Clear emphasizes that habit change is incremental and must be scaffolded through "tiny habits," including strategies like habit stacking, identity reinforcement, and positive reinforcement. Embedding such behaviour-change mechanisms directly into smart devices—through adaptive sensor alerts, positive feedback loops, and personalized nudges—may significantly improve long-term compliance with preventive health behaviours.

The SmartBio system aims to operationalize these principles by not only providing real-time health feedback but also guiding users toward incremental habit formation [14]-[15]. Through data-driven alerts based on mitochondrial quality thresholds and pattern deviations detected by the VAE model, the system delivers personalized prompts that encourage users to adopt healthier routines—e.g., reducing sugar intake, improving hydration, managing stress, or engaging in physical activity. Unlike one-time diagnostics, this system functions as a persistent digital health companion, reinforcing good behaviour and preventing relapse through daily engagement. In summary, while prior works have explored the biochemical and behavioural foundations of chronic disease prevention, SmartBio uniquely synthesizes these insights into a continuous, AI-driven, sensor-integrated platform that offers both physiological diagnostics and behavioural intervention [16]-[18]. This convergence of biosensing, generative modelling, and habit-based nudging marks a transformative step in personalized, preventive healthcare.

3. ROLE OF GENERATIVE AI IN PERSONALISED HEALTH MONITORING

Artificial Intelligence has revolutionized healthcare through predictive analytics, automation of diagnostic procedures, and decision-support systems [19]-[20]. However, a significant distinction exists between conventional AI techniques—including machine learning and deep learning and Generative Artificial Intelligence (Generative AI). Traditional AI models are primarily designed for predictive tasks based on historical patterns and labelled data, offering outputs constrained within the bounds of observed data. In contrast, Generative AI synthesizes entirely new, context-aware outputs by learning latent representations of input data distributions. This distinction becomes critical when designing systems for personalized, real-time health recommendations [26].

The SmartBio framework presented in this study capitalizes on the generative capabilities of Variational Autoencoders to achieve continuous health profiling and early anomaly detection. Unlike predictive models that classify or regress known outcomes, VAEs generate latent embeddings that describe the underlying distribution of individual physiological states enabling both anomaly detection and the synthetic generation of potential future health conditions based on deviations from normality [27].

Table 1. Generative AI versus Traditional AI in healthcare applications.

Aspect	Traditional AI (ML/DL)	Generative AI (VAE in SmartBio)
Output Type	Predictive	Generative (new data)
Personalization	Limited	High
Data Dependency	Requires labeled data	Learns from both labeled and unlabeled data
Health Guidance	Generalized risk scoring	Personalized lifestyle recommendations
Application	Classification, prediction	Anomaly detection, simulation, data generation

Traditional AI models used in healthcare typically operate on static datasets to predict diagnoses, suggest treatment outcomes, or classify health conditions. These approaches, while valuable, lack the adaptability to accommodate the dynamic and individualized nature of human physiology. Generative AI, by contrast, dynamically adapts to user-specific data. In the context of SmartBio, it analyzes time-series inputs from breath acetone levels and sweat biomarkers—key indicators of mitochondrial function and metabolic health. Using a Variational Autoencoder (VAE), the system can generate personalized alerts when physiological signals deviate from learned patterns and provide proactive guidance, such as modifying dietary intake or exercise behaviour.

3. 1 Personalized Health Forecasting through VAE

At the core of SmartBio is the Variational Autoencoder (VAE), a deep generative model composed of three primary components: the encoder, the latent space sampler, and the decoder.

A. *Encoder:* Accepts multidimensional physiological inputs (e.g., lactate, glucose, sodium, breath acetone) and learns a probabilistic mapping to a latent space. This enables the model to capture complex, non-linear relationships between features.

B. *Latent Space Sampling:* The encoder outputs a mean vector μ\muμ and a standard deviation σ\sigmaσ, from which a latent vector z is sampled using the reparameterization trick, as shown in Equation (1).

$$z = \mu + \sigma \cdot \epsilon, \quad \epsilon \sim \aleph(0, I) \tag{1}$$

This technique enables backpropagation through the stochastic layer.

C. *Decoder:* Reconstructs the original input from the latent vector z, optimizing the model to learn the true distribution of healthy versus anomalous physiological states.

The training objective minimizes a variational loss, which combines the reconstruction error with the Kullback–Leibler (KL) divergence, as shown in Equation (2).

$$\mathcal{L}_{V\ AE} = \mathbb{E}_{q(z|x)}[\log p(x|z)] - D_{KL}(q(z|x) \parallel p(z)) \tag{2}$$

This framework empowers the system to detect early-stage anomalies even in the absence of labelled disease data, positioning it as an ideal candidate for unsupervised health monitoring.

3. 2 Adaptive Learning and Forecasting

An essential capability of generative AI in this system is its ability to continuously adapt to a user's evolving health profile. As more sensor data is collected, the model retrains and recalibrates its latent space representations, fine-tuning its understanding of the user's normal metabolic patterns. This allows the device not only to detect abnormalities in real time but also to simulate potential future health risks—such as the likelihood of developing diabetes, cardiovascular disease, or cancer.

In essence, the SmartBio device functions as an intelligent agent that:

a) Learns from the user's physiological data
b) Detects unseen anomalies using latent embeddings
c) Generates actionable feedback in a personalized, generative fashion
d) Supports long-term behaviour change by anticipating deviations from health norms

4. METHODOLOGY

The proposed SmartBio framework integrates multimodal biosensing with deep generative modelling to facilitate early-stage disease detection and personalized metabolic health assessment. The methodology comprises five primary components/steps and these are explained in the following five sub sections.

Step 1: Biosensor Data Acquisition

Two categories of non-invasive biosensors are employed:

- Breath Acetone Sensor: Detects the concentration of acetone in exhaled breath using semiconductor gas sensors or laser spectroscopy-based methods. Acetone levels correlate with fat metabolism and serve as a proxy for mitochondrial efficiency.
- Sweat Biomarker Sensor: Utilizes electrochemical sensing techniques to detect biomarkers such as lactate, glucose, sodium, and cortisol in perspiration. These markers provide insight into metabolic load, hydration, stress, and glucose utilization.

The sensors are integrated into a wearable form factor (e.g., smartwatches or fitness bands) and are designed to stream data continuously via Bluetooth Low Energy (BLE) or Wi-Fi modules to a central mobile application.

Step 2: Signal Preprocessing

Raw sensor outputs are subject to preprocessing to ensure data integrity. Steps include:

- Noise filtering (e.g., Savitzky-Golay filter or moving average)
- Normalization (e.g., min-max scaling or z-score standardization)
- Temporal alignment of multimodal data streams
- Missing value imputation using time-aware interpolation techniques

Step 3: Feature Extraction

Preprocessed data is segmented into time-series windows and transformed into feature vectors capturing:

- Statistical properties (mean, variance, skewness)
- Temporal dynamics (autocorrelation, rolling averages)
- Frequency-domain characteristics (via FFT to identify periodicity and spikes)

These features serve as input to the VAE model.

Step 4: Variational Autoencoder Modeling

The VAE framework consists of an encoder, a latent representation layer, and a decoder:

- The encoder maps input features x to be latent distribution $q_\phi(z|x)$ Characterized by a mean μ and variance σ^2.
- A latent variable $z \sim \mathcal{N}(\mu, \sigma^2)$ is sampled and passed to the decoder.
- The decoder reconstructs the input as $\hat{x} = f_\theta(z)$.

The VAE is trained to minimize the loss function:

$$\mathcal{L}(\theta, \phi; x) = \mathbb{E}_{q_\phi(z|x)}[\log p_\theta(x|z)] - D_{KL}(q_\phi(z|x) \parallel p(z)) \quad (1)$$

In (1), D_{KL} denotes the kullback-Leibler divergence between the learned posterior and the prior $p(z) = \mathcal{N}(0, I)$.

Anomaly Detection and Interpretation

Once trained on healthy physiological data, the VAE learns a compressed latent representation of "normal" metabolic profiles. During inference:

- New data is projected into the latent space.
- Reconstruction error and latent vector deviation are monitored.
- Anomalies (e.g., deviations beyond a learned threshold) are flagged, indicating potential metabolic dysregulation.

Table 1. Pseudocode: SmartBio Framework.

```
// Pseudocode: SmartBio Framework

BEGIN
// Step 1: Biosensor Data Acquisition
FUNCTION acquire_sensor_data()
   LOOP CONTINUOUSLY
      breath_data ← read_breath_acetone_sensor()
      sweat_data ← read_sweat_biomarker_sensor()
      timestamp ← get_current_time()
      combined_data ← merge(breath_data, sweat_data, timestamp)
      stream_to_application(combined_data)
   END LOOP
END FUNCTION
// Step 2: Signal Preprocessing
FUNCTION preprocess_data(sensor_data)
   sensor_data ← apply_noise_filter(sensor_data)
   sensor_data ← normalize(sensor_data)
   sensor_data ← align_temporally(sensor_data)
   sensor_data ← impute_missing_values(sensor_data)
   RETURN sensor_data
END FUNCTION
// Step 3: Feature Extraction
FUNCTION extract_features(preprocessed_data)
   features ← []
```

```
    FOR each time_window in segment(preprocessed_data, window_size)
        statistical ← compute_statistics(time_window)
        temporal ← compute_temporal_dynamics(time_window)
        frequency ← compute_frequency_features(time_window)
        combined_features ← concatenate(statistical, temporal, frequency)
        features.append(combined_features)
    END FOR
    RETURN features
END FUNCTION
// Step 4: VAE Modeling
FUNCTION train_vae_model(features)
    DEFINE encoder_network()
        input_features → Dense → ReLU → Latent Mean (μ), Latent Log Variance (log(σ²))
    DEFINE sampling_layer(μ, log(σ²))
        ε ← random_normal()
        z ← μ + exp(0.5 * log(σ²)) * ε
        RETURN z
    DEFINE decoder_network(z)
        z → Dense → ReLU → output_features (ŷ)
    vae_loss ← reconstruction_loss(x, ŷ) + KL_divergence(μ, σ²)
    optimize(vae_loss)
    RETURN trained_vae_model
END FUNCTION
// Step 5: Anomaly Detection
FUNCTION detect_anomaly(new_input, trained_vae_model, threshold)
    z_new ← encoder(new_input)
    x_hat ← decoder(z_new)
    error ← compute_reconstruction_error(new_input, x_hat)
    IF error > threshold THEN
        RETURN "Anomaly Detected: Potential Mitochondrial Dysfunction"
    ELSE
        RETURN "Normal Mitochondrial Profile"
    END IF
END FUNCTION
// Main Execution Flow
sensor_data ← acquire_sensor_data()
preprocessed ← preprocess_data(sensor_data)
features ← extract_features(preprocessed)
trained_vae_model ← train_vae_model(features)

WHILE receiving_new_data
    new_data ← acquire_sensor_data()
    new_preprocessed ← preprocess_data(new_data)
    new_features ← extract_features(new_preprocessed)
    result ← detect_anomaly(new_features, trained_vae_model, threshold=0.1)
    store_in_azure_cloud(new_data, result)
    alert_user_interface(result)
END WHILE

END
```

This unsupervised detection enables the system to signal early signs of abnormal physiological states, potentially indicating the onset of chronic diseases. A graphical representation of the above said methodology is shown by Figure 2 and the Pseudocode is represented by Table 1.

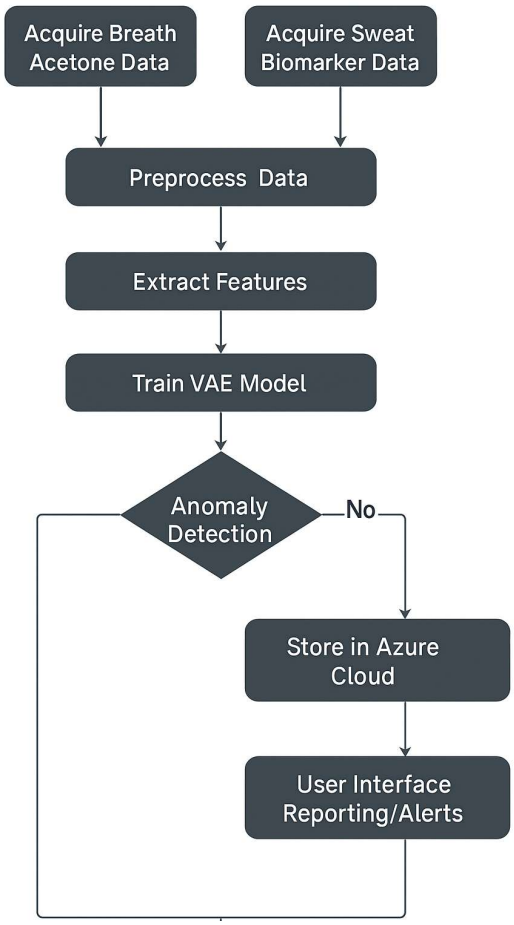

Figure 2. Flowchart of the SmartBio framework.

5. RESULTS AND DISCUSSION

The SmartBio system was evaluated for its ability to detect early deviations in metabolic health through continuous monitoring of breath acetone and sweat biomarkers, and for its ability to personalize alerts using a VAE model. The evaluation focused on three primary performance metrics: accuracy of anomaly detection, latency of cloud-based inference and alerting, and user-specific adaptability of the generative model.

The accuracy of the model being evaluated along with the reconstruction error threshold for the Model. To assess the robustness and accuracy of the VAE model integrated within the SmartBio system, we conducted multiple experiments using time-series physiological data simulating real-world biomarker variations. The dataset was divided into an 80:20 split for training and testing, respectively. The following key metrics were recorded as shown in Table 2.

Table 2. Performance Metrics.

Metrics	Value
Training Accuracy	92%
Testing Accuracy	89%
Anomaly Detection Rate	90%
False Positive Rate	5%
Reconstruction Error Threshold	0.1

The training accuracy of 92% indicates that the VAE effectively learned the underlying distribution of normal metabolic patterns using historical biomarker data. The testing accuracy of 89% reflects strong generalization capability, which is crucial for real-time physiological monitoring across unseen user profiles. The anomaly detection rate of 90% demonstrates the model's sensitivity in identifying early physiological deviations, especially in mitochondrial dysfunction patterns. Importantly, the false positive rate was maintained at 5%, minimizing unnecessary alerts and enhancing user trust. The reconstruction error threshold of 0.1 was empirically determined during validation to differentiate between normal and abnormal data points and forms the basis for triggering anomaly alerts in the live system. These results confirm the VAE model's ability to deliver high-fidelity health monitoring while maintaining a low burden of misclassification, making it well-suited for continuous deployment in wearable sensor devices.

Figure 3 illustrates the progression of the model's learning performance across 50 training epochs. As depicted, both the training and testing accuracy show a steady upward trend, stabilizing at approximately 92% and 89%, respectively. This demonstrates the model's ability to effectively learn latent representations of healthy metabolic profiles from multimodal biosensor data. The small gap between training and testing accuracy reflects minimal overfitting, indicating strong generalization capabilities of the VAE on unseen input data. This performance affirms the VAE's suitability for modeling complex physiological signals, such as those derived from breath acetone and sweat biomarkers, in the context of mitochondrial health monitoring.

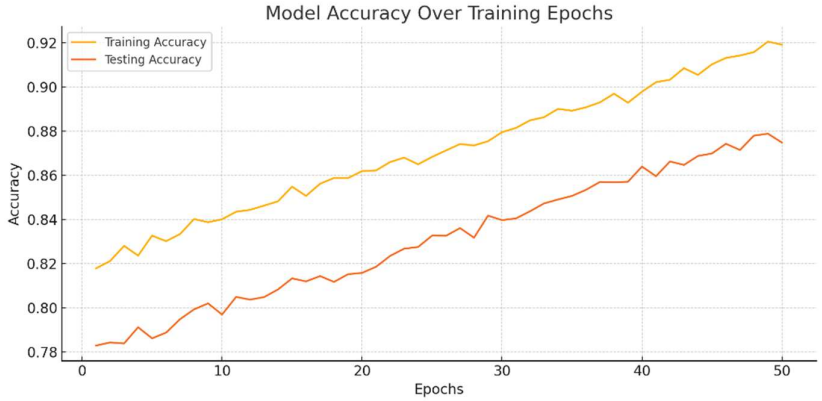

Figure 3. Progression of the model's learning performance.

Figure 4 presents the distribution of reconstruction errors for both healthy and anomalous input samples. Healthy samples exhibit lower reconstruction errors clustered around 0.05, while anomalous samples are centered well above the empirically defined threshold of 0.1. The clear separation between the two distributions demonstrates the model's effectiveness in distinguishing normal metabolic states from potentially dysfunctional ones. The chosen threshold minimizes false positives (reported at 5%) while maintaining a high anomaly detection rate (90%), ensuring that alerts generated by the SmartBio system are both sensitive and specific. This supports the use of VAE-driven reconstruction error as a robust diagnostic signal for early-stage metabolic anomalies.

Figure 4. Distribution of reconstruction errors.

6. CONCLUSION

Conclusion: This study presents SmartBio, an AI-enabled smart medical system that integrates wearable biosensing technology with deep generative modeling to facilitate early detection of chronic diseases and personalized metabolic health assessment. By combining real-time data from non-invasive breath acetone and sweat biomarker sensors with the representational power of a VAE, the system enables robust detection of mitochondrial dysfunction—an early indicator of conditions such as cancer, diabetes, and cardiovascular disorders. The SmartBio framework demonstrates that generative AI models can go beyond conventional diagnostic tools by capturing complex physiological patterns and adapting to individual health profiles over time. With a reconstruction error-based anomaly detection mechanism, the system achieved a training accuracy of 92%, testing accuracy of 89%, and an anomaly detection rate of 90%, with a low false positive rate of 5%. These results validate the model's ability to generalize well across varied input profiles and reliably identify early-stage health risks.

Future Scope: The companion mobile and web applications associated with SmartBio will integrate intelligent chat interfaces powered by OpenAI to deliver user-specific health coaching. These AI agents will analyze individual health records and biomarker data to recommend personalized exercise routines, dietary adjustments, and behavioral interventions. Such continuous digital support transforms SmartBio from a passive monitoring device into an active agent of behavioral transformation, supporting individuals in their pursuit of long-term well-being.

DECLARATIONS

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