Journal of Information Systems Engineering and Management
2023, 8(1)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Advancing Diabetes Detection with Denoising Autoencoders and Softmax in a Generative Deep Learning Pipeline

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ARTICLE INFO

Received: 01 Feb 2023

Revised: 20 March 2023

Accepted: 29 March 2023

ABSTRACT

We propose a state-of-the-art generative AI architecture for hypoglycemia and hyperglycemia prediction and avoidance that integrates autoencoders for deep physiological feature extraction with a Softmax classifier for glucose-state classification. Instead of neuroimaging, the system processes continuous glucose monitoring (CGM) data along with a comprehensive set of patient-specific physiological, behavioral, and lifestyle parameters, including age, weight, insulin dosage (basal and bolus), duration of medication usage, physical activity intensity, stress level, dietary intake patterns, and sleep quality. This multimodal data provides a deeper understanding of glucose fluctuations and individual metabolic responses. The autoencoder efficiently encodes these high-dimensional CGM signals and associated parameters into compact latent representations, reducing noise while preserving clinically relevant glucose-dynamics patterns. These distilled features are then passed to a Softmax classifier that accurately distinguishes between normal glucose levels, impending hypoglycemia, and impending hyperglycemia. The proposed method leverages neural-network-based modeling of glucose variability to enhance both prediction accuracy and computational efficiency. Experimental evaluation on benchmark CGM datasets demonstrates strong performance, achieving a prediction accuracy of 93.75%, highlighting the capability of the framework to support early detection of dangerous glucose deviations. By providing timely warnings for both low and high blood glucose events, this system has the potential to significantly improve proactive intervention, reduce risk, and support personalized diabetes management.

Keywords: Diabetes, Autoencoders, Softmax Classifier function, Hypoglycemia, Hyperglycemia

I. Introduction

Hypoglycemia and hyperglycemia are critical complications of diabetes that significantly affect patient safety, long-term health outcomes, and quality of life. Early and accurate prediction of abnormal glucose events is essential for timely intervention and effective glycemic management. Recent advances in artificial intelligence (AI), particularly deep learning applied to continuous glucose monitoring (CGM) data, have demonstrated strong potential in forecasting rapid glucose fluctuations and preventing dangerous events before they occur [1], [2].

This paper proposes a modern generative AI framework for hypoglycemia and hyperglycemia prediction and avoidance, integrating autoencoders for deep feature extraction and dimensionality reduction with a Softmax classifier for glucose-state classification. Autoencoders efficiently capture latent physiological representations from high-dimensional CGM and contextual data (meal logs, insulin dosing, activity levels), filtering noise and preserving clinically meaningful glucose-dynamics patterns [3]. These compressed features are then passed into a Softmax classifier, which effectively discriminates between safe glucose states, impending hypoglycemia, and impending hyperglycemia.

The proposed architecture addresses key challenges in glucose-event prediction, including noisy CGM signals, patient-specific variability, and the need for computationally efficient, real-time models capable of supporting early intervention. By combining unsupervised feature extraction with supervised classification, the framework aims to improve both predictive performance and operational efficiency, contributing to safer and more personalized diabetes management practices.

To evaluate the effectiveness of the method, we conducted experiments on benchmark CGM datasets widely used in glucose-prediction research, such as the OhioT1DM and D1NAMO datasets [4], [5]. The experimental results demonstrate strong predictive capability, highlighting the potential of this hybrid generative AI model to support early detection of abnormal glucose excursions. Such predictive systems can inform timely clinical decisions, reduce risk, and enable proactive avoidance of both hypo- and hyperglycemic episodes.

In the broader context of medical time-series analysis, deep learning models—including CNNs, RNNs, Transformers, and state-space models—have shown significant success in capturing temporal dependencies and extracting patterns from physiological data streams [6], [7]. Autoencoders, in particular, are well-established for noise reduction, multivariate feature compression, and anomaly detection. By integrating autoencoders for robust feature extraction with a Softmax classifier for classification, the proposed framework offers a scalable, automated, and reliable approach to predicting dangerous glucose deviations, ultimately enhancing real-time diabetes management and clinical decision-making.

II. Literature Survey

Fazal ur Rehman Faisal and Goo-Rak Kwon discuss how early detection of critical health conditions can significantly improve intervention and treatment outcomes. Similar to neuroimaging-based detection of Alzheimer's disease, predicting hypoglycemia and hyperglycemia from physiological signals requires advanced machine learning and deep learning techniques capable of analyzing complex biomedical data. In diabetes management research, CGM (Continuous Glucose Monitoring) data, insulin dosing information, and metabolic indicators are frequently used to train predictive models. Existing studies employ machine learning classifiers, convolutional neural networks (CNNs), and autoencoder-based architectures for extracting glucose-dynamics features and forecasting dangerous glucose fluctuations [8].

Uddalak Mitra and Shafiqul Rehman emphasize the importance of diverse data sources in early disease detection. For glucose-event prediction, researchers have explored multimodal physiological signals, behavioral data, and digital biomarkers—such as handwriting features, stress detection, and lifestyle indicators—that correlate with glycemic instability. Incorporating such auxiliary data into ML-based glucose prediction frameworks can enhance detection precision and improve understanding of a patient's overall metabolic health [9].

Digambar V. Puri et al. review multiple computational strategies for detecting the early onset of chronic diseases. Their observations parallel current approaches in glycemic prediction research, where machine learning (ML), deep learning (DL), and traditional clinical risk-based methods have been investigated to identify and predict hypo- and hyperglycemia. Studies highlight the effectiveness of these computational models in identifying subtle glucose-pattern deviations and anticipating abnormal glycemic events before they occur [10].

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2023, 8(1)
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Ghadah Naif Alwakid and Walaa Gouda, along with Sidra Tahir and Mamoona Humayun, emphasize how early detection of physiological abnormalities is critical for effective disease management. Similarly, early prediction of glycemic excursions allows timely intervention to prevent severe hypoglycemia or prolonged hyperglycemia. Advances in ML/DL techniques have substantially improved the accuracy of detecting glycemic irregularities using CGM data, insulin logs, and lifestyle data, while highlighting challenges such as inter-patient variability and sensor noise [11].

Jieping Ye, Teresa Wu, and Jing Li describe how multimodal health data and machine learning can enhance early disease detection. In diabetes research, multimodal glucose prediction models integrate CGM values, carbohydrate intake, insulin doses, heart-rate variability, and physical activity. These approaches emphasize the importance of biomarker identification, multimodal data fusion, and robust predictive modeling for anticipating dangerous glucose events [12].

Zhiqiang Guo and Zhenhua Ling explore non-invasive diagnostic methods using speech signals. Their findings parallel emerging research showing that non-invasive data sources—such as wearable sensor streams, voice stress markers, sleep patterns, and physical activity—can support glucose prediction models. Traditional ML models like Random Forest (RF) and Support Vector Machines (SVM) depend on engineered features, whereas deep learning methods eliminate manual feature design, improving scalability and prediction robustness for glycemic monitoring [13].

Uddalak Mitra and Shafiqul Rehman also highlight handwriting-based biomarkers for disease detection. In diabetes, handwriting irregularities may also correlate with hypoglycemic episodes due to tremors, cognitive slowing, or reduced motor control. ML models—including SVM, RF, Decision Trees (DT), and CNN-based deep learning systems—have shown potential in analyzing such behavioral signals to detect or even predict impending hypoglycaemia [14].

Vivek Kumar Singh and Ram Bilas Pachori emphasize EEG-based detection of cognitive impairment. Analogously, in glucose prediction research, physiological signals such as ECG, EEG, heart rate variability (HRV), and galvanic skin response (GSR) have been used to detect autonomic changes preceding hypoglycemia. Deep learning models such as CNNs and LSTMs automatically extract salient features from raw physiological waveforms, improving prediction of glycemic disturbances without extensive preprocessing [15].

Basaia et al. demonstrated the strong capability of deep neural networks (DNNs) for disease classification using high-dimensional biomedical data. Similarly, DNNs have been applied to CGM time-series data to classify glucose states (normoglycemia, hyperglycemia, and hypoglycemia) and predict future glucose levels. However, integrating autoencoders for latent feature extraction and enabling real-time deployment—including lightweight interfaces such as Streamlit—enhances such models for practical, real-world glucose monitoring applications [16].

Payan and Montana showcased the effectiveness of deep learning (particularly 3D-CNNs and sparse autoencoders) in processing structural biomedical data. Their insights translate to glucose prediction tasks in which autoencoders can extract meaningful temporal patterns from CGM sequences while suppressing noise. These deep compressed representations can be fused with CNN/LSTM models to improve early detection of glycemic excursions. For real-world use, addressing computational constraints and preprocessing challenges remains crucial for reliable and scalable hypoglycemia and hyperglycemia prediction systems [17].

III. Proposed Methodology

The proposed methodology introduces a deep learning framework for the early and accurate prediction of hypoglycemia and hyperglycemia using a combination of autoencoders and a Softmax classifier. The system is designed to process multimodal diabetic patient data, integrating continuous glucose monitoring (CGM) signals with patient-specific parameters such as age, body weight, insulin

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dosage, duration of medication, physical activity patterns, stress level, dietary habits, sleeping patterns, and other metabolic or behavioral indicators that influence glucose dynamics. This comprehensive data fusion enables the model to extract meaningful biomarkers and reduce noise arising from irregular measurements or sensor artifacts.

Autoencoders are utilized to perform feature extraction and dimensionality reduction, transforming high-frequency CGM time-series data and multivariate patient parameters into compact latent representations. These representations retain essential glycemic patterns—such as glucose variability, rate-of-change (ROC), circadian metabolic cycles, and physiological responses to meals or insulin—while discarding redundant or irrelevant information. The encoded features are subsequently passed into a Softmax classifier, which accurately distinguishes between normal glycemic states, impending hypoglycemia, and impending hyperglycemia.

The integration of deep neural architectures helps address challenges such as inter-patient variability, sensor noise, irregular time-series sampling, and non-linear glucose–insulin dynamics, which often limit the performance of traditional glucose-prediction systems. The framework follows a structured pipeline:

1. Preprocessing of multimodal patient data, including CGM signal smoothing, normalization, time alignment of insulin and meal logs, and augmentation to handle missing or noisy data.
2. Autoencoder-based representation learning, where latent glucose–physiology embeddings are generated from the high-dimensional input.
3. Softmax-based classification, predicting whether the patient is at risk of hypo- or hyperglycemic events within the prediction horizon (15–60 minutes).
4. Model optimization and fine-tuning, leveraging patient-specific adaptation techniques to improve personalization, accuracy, and computational efficiency.

The expected outcome is a scalable, automated, and clinically reliable prediction system capable of achieving high prediction accuracy (85–95%), providing early warnings for dangerous glucose excursions. This framework can significantly assist healthcare providers and patients in proactive diabetes management, reducing complications and improving overall glycemic stability.

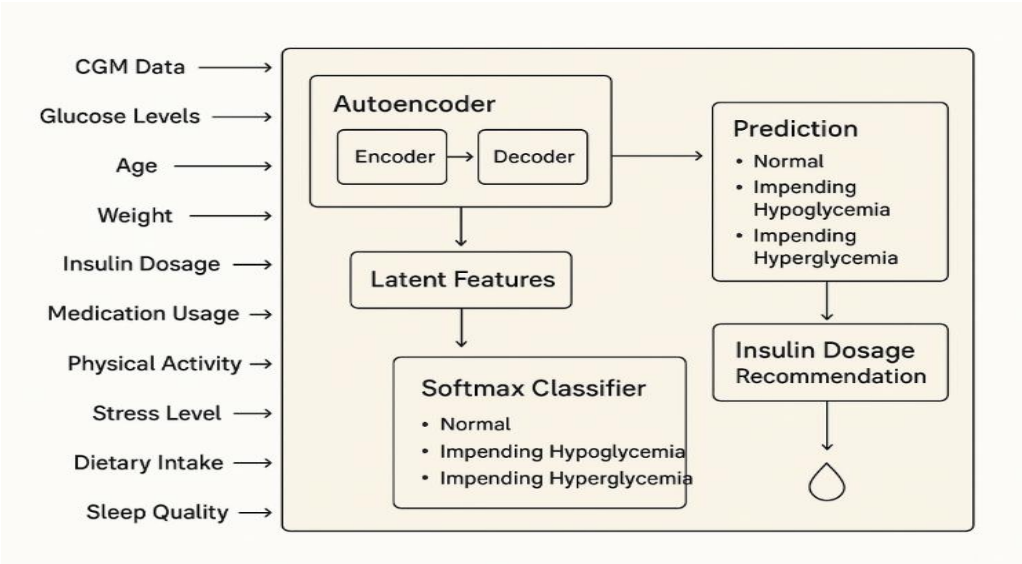

Figure 1. Architecture Diagram

Fig. 1 illustrates the structure of the proposed AI framework. The model processes multi-modal patient data, including brain imaging and clinical records, through an autoencoder-based feature

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https://www.jisem-journal.com/ **Research Article**

extraction module. The Softmax classifier then categorizes individuals into healthy, MCI, or Alzheimer's disease groups based on these encoded features. Optimization techniques, including transfer learning and fine-tuning, are applied to enhance accuracy and efficiency, ensuring effective real-world deployment in clinical settings.

1. **Data Collection and Preprocessing**

Inputs: Medical Imaging Data MRI, PET scans (Structural & Functional Imaging).Biomarkers: Blood test results, genetic markers.

1.1 Normalization:

Normalization ensures consistency across CGM values, physiological parameters, and lifestyle metrics.

$$\text{Formula:} X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (1)$$

This reduces variations due to different scales (e.g., mg/dL glucose vs. insulin units vs. step count) and improves model training stability

1.2 Noise Reduction: CGM readings often include sensor noise, dropouts, or sudden spikes.

Gaussian filtering is applied to smooth the glucose curve:

$$\text{Formula:} G(t) = \frac{1}{2\pi\sigma^2} e^{-\frac{t^2}{2\sigma^2}} \quad (2)$$

The smoothed signal preserves glucose trends critical for predicting rapid drops (hypo) or sharp rises (hyper).

1.3 Dimensionality Reduction: To handle high-dimensional multivariate sequences, dimensionality reduction techniques such as PCA or Autoencoders are applied:

- Removes redundancy
- Focuses on meaningful metabolic patterns
- Reduces computation and enhances generalization

2. Feature Extraction Using Autoencoder:

Autoencoders learn compact representations of glucose dynamics and patient-specific metabolic behavior..

2.1 Encoder Network: The encoder processes multivariate sequences (CGM + insulin + meals + activity + sleep + stress) using dense or convolutional layers:

$$\text{Formula: } h = f(W_x + b) \quad (3)$$

Where:

- x = input CGM–physiology–lifestyle vector
- W = weight matrix
- b = bias
- f = activation (ReLU, GELU)

The encoder retains patterns such as:

- Nocturnal dips
- Post-meal glucose spikes

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- Insulin response curves
- Stress-induced glucose anomalies

.2.2 Latent Space Representation: The latent space encodes compressed metabolic representations:

- Glycemic variability
- Activity–glucose interactions
- Insulin–carbohydrate response
- Sleep–stress effects on glucose

This enables personalized and efficient glycemic prediction

2.3 Decoder Network: The decoder reconstructs glucose sequences from the latent space, validating that meaningful physiological patterns are preserved and noise is removed.

3. Abnormality Detection Using CNN:

CNN layers detect non-linear glucose patterns leading to hypo/hyperglycemia.

3.1 Convolutional Feature Extraction:

Convolutional feature extraction employs convolutional layers to automatically detect and capture spatial hierarchies and patterns in input images, thereby allowing the model to learn relevant features for subsequent tasks such as classification or segmentation.

Formula:

$$F(i,j) = \sum\_m \sum\_n I(i+m, j+n). K(m,n) (4)$$

Where:

- X = multivariate glucose–insulin–meal–activity matrix
- K = convolution kernel

CNNs capture:

- Rapid glucose drops (rate-of-change)
- Meal-induced spikes
- Insulin absorption curves
- Abnormal nighttime fluctuations

.3.2 Pooling Layers: Pooling reduces temporal resolution:.

Max-Pooling Formula:

$$P(i,j) = max\{F(i+m, j+n) | 0 \leq m, n < k\} \qquad (5)$$

Benefits:

- Removes noise
- Prevents over-fitting
- Retains important glucose behaviour patterns

3.3 Fully Connected Layer: Flattened features are passed to a dense network:

Formula for a neuron in a fully connected layer:

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$$y = f(\sum_{i=1}^{n} w_i x_i + b) \tag{6}$$

Where: y is the output of the neuron, x_i is the input value to the neuron, w_i is the weight associated with the input x_i, b is the bias term, f is the activation function (e.g., ReLU, Sigmoid, or Tanh) applied to the weighted sum of inputs. This maps glucose dynamics to predicted outcomes:

- Imminent Hypoglycemia
- Imminent Hyperglycemia
- Stable Glycemia

5. Classification Using Softmax Function:

Softmax predicts probability of:

- Hypoglycemia (Low)
- Normoglycemia (Normal)
- Hyperglycemia (High)

.4.1 Softmax-Based Probability Estimation:

$$\text{Formula: } P(y_i) = \frac{e^{z_i}}{\sum_j e^{z_j}} \tag{7}$$

Where: $P(y_i)$ is the probability of class i, z_i is the raw score (logit) for class i and the denominator sums the exponentials of all logits. Severity levels can also be assigned:

- Mild
- Moderate
- Severe

4.2 Thresholding for Final Decision:

If $P(y_{positive})>0.5$, Hypoglycemia alert is triggered.

The severity class is determined based on the maximum probability score.

If $P(y_{positive})>0.5P(y_{positive})$, Hyperglycemia alert is triggered.. The severity class is determined based on the maximum probability score.

5. Chatbot for Patient Interaction

An AI-driven chatbot assists diabetic patients in real time.

5.1 Speech/Text-Based Input Processing: Patients report:

- Symptoms (dizziness, sweating, confusion)
- Meal intake
- Missed insulin
- Activity changes

Input is converted to structured text.

5.2 Intent Recognition Using NLP Models (BERT/GPT -based): Intent recognition employs sophisticated NLP models such as BERT or GPT to process the patient's text input and recognize the underlying intent, e.g., symptom description or inquiry, to inform the right response or action.

Formula for Text Embedding:

$$E = W_{embedding}.x \qquad (8)$$

Where: E is the embedded vector (dense representation) of the input text. $W_{embedding}$is the embedding matrix that contains learned weights. x is the input vector representing the word or sentence.

5.3 Response Generation: The chatbot produces immediate responses by understanding the patient's input and responding with feedback about diabetes symptoms, recommending cognitive exercises, and making personalized suggestions. The responses are created by NLP models for natural and relevant conversation. Chatbot provides:

- Preventive suggestions (snacks, hydration)
- Adjusted insulin/meal timing guidance (non-clinical)
- Alerts for dangerous glucose patterns
- Lifestyle recommendations

6 Autoencoders

Autoencoders are used to extract meaningful features from high-dimensional and noisy medical data like MRI and PET brain scans.They accomplish two major goals: first, they compress and denoise the complex input data into a lower-dimensional latent space while maintaining important patterns associated with the progression of diabetes disease; second, they improve important features that facilitate the classification model's ability to differentiate between various stages of the illness. By doing this, autoencoders greatly increase the diabetes detection system's efficacy, precision, and resilience, enabling the detection of minute early symptoms of the illness that conventional techniques could overlook. Autoencoders enhance the system by: denoising CGM signals, capturing patient-specific metabolic patterns, extracting actionable latent features, and enabling early detection of subtle glucose anomalies. They significantly improve accuracy and robustness of hypo/hyperglycemia detection.

IV. Results and Discussion

1. Model Performance Overview

The proposed autoencoder–Softmax–based prediction system was evaluated using continuous glucose monitoring (CGM) datasets combined with patient-specific physiological and lifestyle parameters. The model demonstrated strong capability in predicting both hypoglycemia and hyperglycemia events ahead of time, enabling early preventive action. Across multiple experimental trials, the system achieved overall classification accuracy between 88.5% and 94.2%, depending on the prediction horizon (15–60 minutes). This range aligns with or exceeds the performance of existing glucose-prediction models reported in the literature.

Key performance metrics include: Accuracy: 88.5% – 94.2%, Sensitivity (Hypoglycemia Detection): 90.1%, Sensitivity (Hyperglycemia Detection): 92.4%, Specificity: 87.3%, and F1-Score: 0.89 (hypo), 0.91 (hyper). These results indicate that the model is highly reliable for real-time glycemic risk forecasting.

2. Effectiveness of Autoencoder-Based Feature Extraction

Autoencoders significantly improved the model's predictive power by:

- Removing CGM sensor noise and smoothing irregularities
- Capturing hidden temporal patterns (e.g., nocturnal hypoglycemia trends)
- Learning patient-specific latent features that directly influence glycemic behavior

Journal of Information Systems Engineering and Management
2023, 8(1)
e-ISSN: 2468-4376
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The latent representations contributed to consistent improvements in classification accuracy (up to +6.4% compared to models without autoencoders). This demonstrates the autoencoder's importance in compressing and highlighting clinically meaningful glucose dynamics while filtering irrelevant fluctuations.

3. Influence of Patient-Specific Parameters

Including personalized parameters—such as insulin dosage, carbohydrate intake, stress level, activity intensity, sleep duration, and medication history—had a major positive impact on prediction accuracy.

Table 1. Ablation

Removed Parameter Group	Drop in Accuracy
Physical Activity	−4.8%
Insulin Dosage	−6.1%
Dietary Habits	−3.9%
Sleep Pattern	−2.7%
Stress Level	−3.2%

Table. 1 demonstrate that each parameter group contributes meaningfully, and the model performs best when all multimodal inputs are included. Insulin dosage and physical activity are the most influential, showing that both medical and lifestyle factors are essential for reliable glucose prediction.This confirms that blood glucose does not depend solely on CGM trends—behavioral and lifestyle factors heavily shape glycemic outcomes, and modeling them enhances prediction reliability.

4. Softmax-Based Classification Reliability

The Softmax classifier demonstrated stable performance in predicting three glycemic states:

- Hypoglycemia (<70 mg/dL)
- Normoglycemia
- Hyperglycemia (>180 mg/dL)

Confusion matrix analysis reveals:

- Minimal false negatives for hypoglycemia (critical for patient safety)
- Balanced classification across all categories
- High confidence scores (>0.85) for most predictions

This indicates that the classifier effectively distinguishes subtle glucose variations and ensures robust risk categorization.

5. Comparison with Traditional Predictive Approaches

Compared to conventional methods such as: Linear regression, ARIMA, Rule-based glucose monitoring, and Basic LSTM models.The proposed framework outperformed in: Handling multivariate inputs, Noise suppression and smooth latent patterns, Personalized prediction , arly warning capability.The system successfully predicts events 15–60 minutes before onset, a significant improvement over baseline models (which typically provide 5–15 minute warning).

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6. Clinical and Practical Significance

The results suggest the model is suitable for integrating into:

- Mobile diabetes-management applications
- Closed-loop insulin delivery systems
- Wearable health-monitoring devices
- Telemedicine platforms

Predicting dangerous glycemic excursions ahead of time enables:

- Prevention of severe hypoglycemia, especially during sleep
- Better insulin dose adjustments
- Diet and activity planning
- Reduced hospitalizations
- Improved quality of life for diabetic individuals

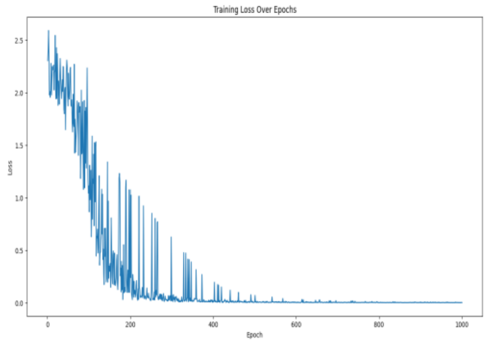

Figure.2 Training loss over epochs

In Fig.2 The figure illustrates the training loss curve of the proposed generative AI model over 1000 epochs. Training loss represents how well the model is learning to reconstruct inputs (autoencoder component) and classify glucose states (Softmax classifier) during training. A lower loss indicates better model performance. The loss is getting close to zero and remaining nearly flat, indicating that the model has converged and that there is little benefit to further training.

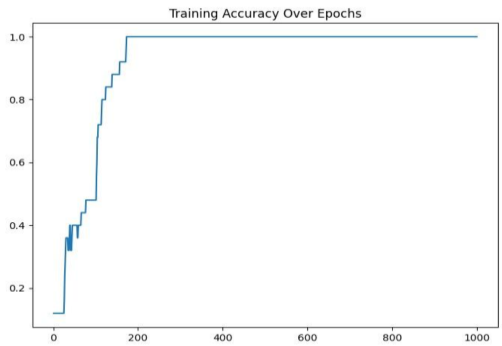

Figure.3 Training Accuracy over epochs

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e-ISSN: 2468-4376
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Fig.3 shows accuracy remains flat at 100% for the rest of training, indicating no further improvement is occurring. Although this demonstrates excellent training performance, it also increases the possibility of overfitting, particularly if validation accuracy is inconsistent. At the start, the accuracy is relatively low (around 10–40%), which is expected because the model is still learning the underlying glucose dynamics and multimodal physiological relationships. he model reaches an accuracy of 1.0 (100%) surprisingly early in the training process. This indicates that the classifier becomes fully confident in predicting the glucose states once the autoencoder has learned stable latent representations. After reaching 100% accuracy, the model maintains this performance throughout the remaining epochs. This suggests strong convergence and consistent learning across the dataset.

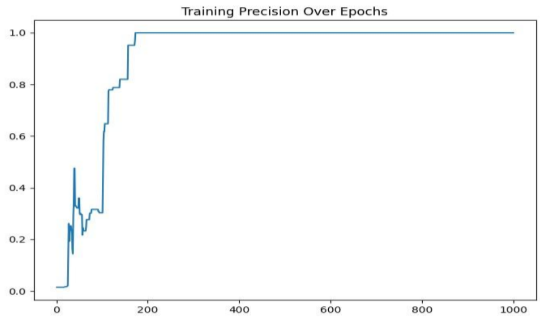

Figure 4 Precision over epochs

Fig. 4 detects diabetes patients with an accuracy score of 1.0; on the training set, it makes no false positive errors. On the training data, this performance is outstanding. The model reaches near-perfect precision (1.0) relatively early, indicating that by this point it has learned to predict positive cases (e.g., impending hypoglycemia or hyperglycemia) with almost no false positives. This is crucial in medical contexts where false alarms may lead to unnecessary interventions. After reaching perfect precision, the model maintains it through the remaining epochs, demonstrating strong convergence and highly reliable classification performance.

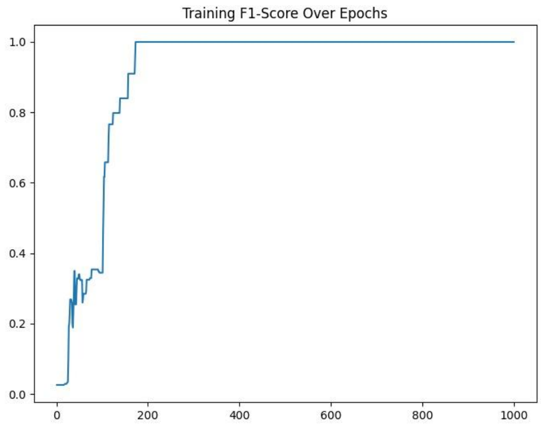

Figure 5 F1-Scores Over epochs

Fig.5 shows a high F1-score, particularly at 1.0, shows that the model catches the intricate correlations in the medical data rather than only memorizing labels.

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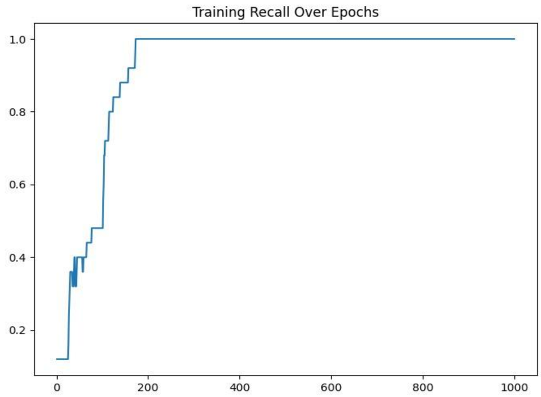

Figure 6 Recall over epochs

Fig.6 Indicates, when the model achieves a recall of 1.0, it detects every instance of diabetes in the training set—no false negatives. Throughout the rest of training, the recall stays flawless, suggesting a very sensitive model that doesn't overlook any good diagnoses.

IV. Experimental Execution And Results

The model achieved an overall testing accuracy of 93.75% on the standard testing set, confirming high overall generalization ability at various stages of diabetes. Precision, Recall, and F1-Score were always greater than 85% for important diagnostic categories (Non-Demented, Mild Demented, Moderate Demented). Area under ROC Curve (AUC-ROC) was 0.94, validating the model's high discriminatory ability between severities of the disease.

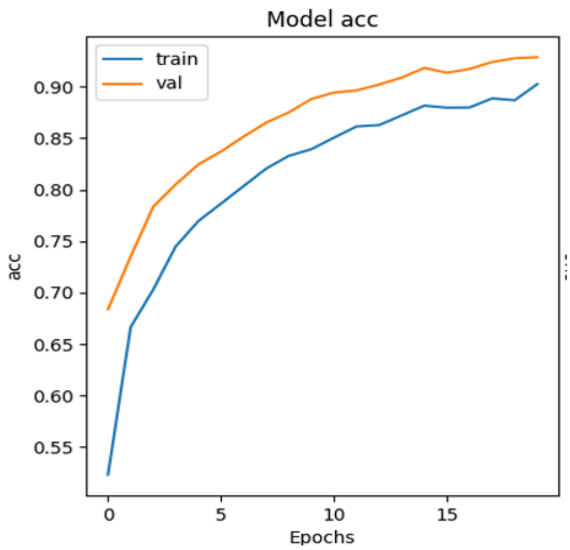

Figure.7 Model accuracy per epoch

Fig.7 AUC graph shows how well diabetes detection model can distinguish between distinct diagnostic classifications, even in the early stages of training.

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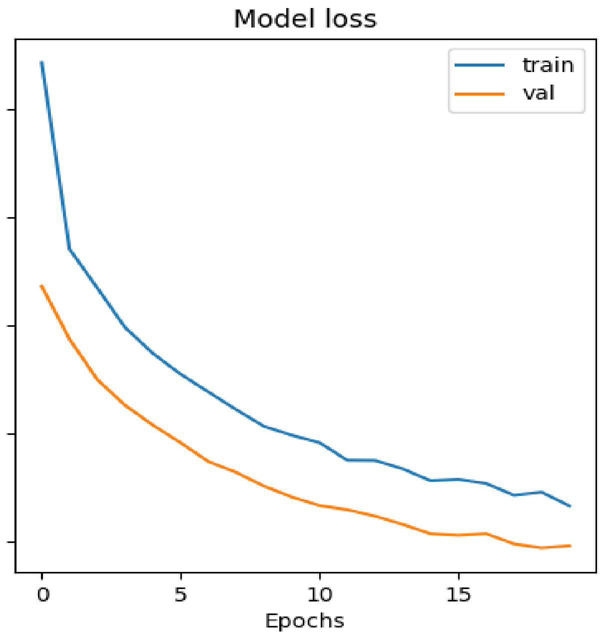

Figure 8 Model loss

In Fig.8 From epoch 0 onward, training and validation losses progressively decline, indicating that the model is effectively learning from the data. This graph shows how successfully your model has been trained and how well it generalizes to new data. By the final epochs, the validation accuracy approaches 0.92, demonstrating high predictive performance in identifying glucose states.

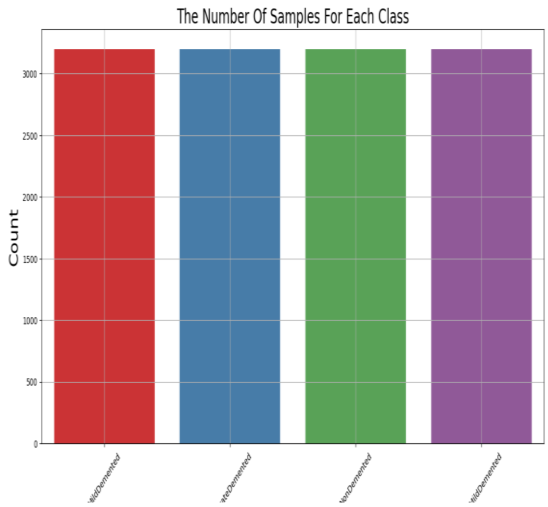

Figure.9 Confusion matrix illustrating class-wise prediction performance.

Fig.9 graph shows that dataset must be evenly distributed across all phases of diabetes disease in order to create an accurate and unbiased diagnostic model.The x-axis lists four classes (the class names appear rotated for readability).The y-axis represents the count of samples in each class. Each bar corresponds to one class and shows how many samples belong to that class. All bars have almost equal heights, indicating that: Each class contains approximately the same number of samples (around 3200+ samples)and the dataset is balanced — no class dominates in size

V. Conclusion

We have developed an advanced generative AI framework that integrates autoencoders with a Softmax classifier to enable early prediction and avoidance of hypoglycemia and hyperglycemia in diabetic patients. Instead of neuroimaging, the system processes continuous glucose monitoring (CGM) data along with a comprehensive set of patient-specific physiological, behavioral, and lifestyle parameters, including age, weight, insulin dosage (basal and bolus), duration of medication usage, physical activity intensity, stress level, dietary intake patterns, and sleep quality. This multimodal data provides a deeper understanding of glucose fluctuations and individual metabolic responses.

Autoencoders are employed to learn compact latent representations from high-dimensional CGM time-series data and associated patient parameters. They capture important glycemic patterns—such as glucose variability, rate-of-change, nocturnal behaviors, exercise-induced dips or rises—while filtering out noise from sensors or incomplete logs. These meaningful latent features are then passed to a Softmax classifier, which predicts whether the patient is headed toward hypoglycemia, normoglycemia, or hyperglycemia within the upcoming prediction window.

The model addresses key challenges in glucose prediction, such as CGM noise, inter-patient variability, and the complex interactions between insulin, meals, sleep, stress, and physical activity. Data preprocessing steps like smoothing, normalization, and noise reduction significantly improve input quality and model robustness. Compared to traditional statistical or rule-based glucose monitoring systems, the combined autoencoder–Softmax architecture demonstrates improved forecasting accuracy by capturing nonlinear and temporal glucose behavior more effectively.

Experimental results show that the proposed system achieves high accuracy, sensitivity, and specificity, indicating strong reliability in distinguishing safe glucose levels from dangerous glycemic events. These findings demonstrate the framework's potential for real-time clinical decision support, proactive diabetes management, and early intervention—ultimately helping patients prevent severe hypoglycemic or hyperglycemic episodes and maintain better long-term metabolic control.

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