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**ABSTRACT**

Diabetes management requires precise insulin dosing, where incorrect predictions can lead to severe health consequences. This project proposes a hybrid deep learning approach for predicting short-acting insulin doses using the AIM94 dataset, which includes glucose measurements, insulin administration, meal ingestion, exercise activity, and hypoglycemic symptoms.

The proposed model integrates Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) architectures in a hybrid design to capture both short-term fluctuations and long-term dependencies in insulin response, along with LSTM-Transformer and GRU-Transformer models for comparison. The dataset underwent a comprehensive preprocessing pipeline, including glucose event transformation into a time series, cyclic encoding of time features, and creation of lag-based features to capture historical insulin dependencies. These techniques, combined with normalization, enhanced the models' ability to predict the dynamic nature of insulin regulation.

Experimental evaluation reveals that the LSTM-GRU hybrid model outperforms individual architectures, achieving an R² score of 0.62, MAE of 1.43, and MSE of 8.29. This model exhibits superior predictive performance by reducing MAE from 1.7 (LSTM-Transformer) and 1.84 (GRU-Transformer) to 1.43, while increasing the R² score from 0.53 in both standalone models to 0.62. The hybrid model's improved accuracy makes it a better choice for predicting insulin doses, helping patients with more reliable results.

***Keywords:*** *Insulin Dose Prediction, Diabetes Management, AIM94 Dataset, LSTM-Transformer, GRU-Transformer, Hybrid Deep Learning.*

**CHAPTER-1**

**INTRODUCTION**

* 1. **Origin of the Problem**

Diabetes is a chronic metabolic disorder that affects millions worldwide and requires continuous monitoring and precise insulin administration to maintain glycemic control. Among various insulin types, short-acting (regular) insulin plays a critical role in managing postprandial glucose spikes. However, determining the appropriate dose remains a complex task, influenced by fluctuating blood glucose levels, meal intake, physical activity, and individual physiological responses. Inaccurate dosing can lead to hypoglycemia or hyperglycemia, posing severe health risks, including coma or long-term organ damage.

In clinical practice, healthcare professionals often rely on empirical judgment and patient-reported data to make dosing decisions. While this method works in supervised settings, it becomes unreliable in outpatient care or for patients managing their condition independently. The lack of real-time, personalized support tools contributes to poor glycemic control and increases the burden on both patients and clinicians. Traditional machine learning models offer limited adaptability in capturing the dynamic and temporal nature of insulin-glucose interactions, especially across diverse patient populations.

To address this challenge, there is growing interest in leveraging advanced deep learning techniques for personalized insulin dose prediction. By capturing both short-term glucose fluctuations and long-range temporal patterns, hybrid sequential models can offer enhanced prediction accuracy and clinical relevance. This project focuses on utilizing the AIM94 data set, which contains detailed, temporally structured clinical records, to train and evaluate deep learning models for insulin dose prediction. The objective is to develop a robust AI-driven solution that supports clinicians and patients in making informed insulin dosing decisions, ultimately improving diabetes management outcomes.

* 1. **Basic definitions and Background**
     1. **Insulin Dose Prediction:** Insulin dose prediction refers to estimating the appropriate quantity of insulin, particularly short-acting insulin, needed to regulate blood glucose levels in diabetic patients. This task is crucial in diabetes management as incorrect dosing may result in hypoglycemia or hyperglycemia, posing significant health risks. Predictive modeling in this context involves learning patterns from clinical events like glucose measurements, meal timing, physical activity, and prior insulin administration.
     2. **Recurrent Neural Networks (RNNs):** Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU), are deep learning models tailored for sequential data. They can learn temporal dependencies, making them suitable for modeling time-series healthcare data like glucose fluctuations. LSTM networks are designed to capture long-term dependencies through memory cells and gating mechanisms, while GRUs offer a more streamlined structure with fewer parameters and comparable performance. Both models are widely used in healthcare prediction tasks due to their ability to learn from patterns in patient history over time.
     3. **Transformer-Based Architectures:** Transformers are deep learning models initially developed for natural language processing but have shown great potential in time-series forecasting. Unlike RNNs, transformers rely on self-attention mechanisms to model relationships across entire sequences simultaneously. This makes them powerful for capturing long-range dependencies in complex temporal data, such as insulin response influenced by events hours earlier. In medical applications, transformer-based models can efficiently process sequences and highlight temporal dynamics that may be overlooked by traditional models.
     4. **Hybrid Deep Learning Models:** Hybrid models combine the strengths of multiple deep learning architectures to improve learning performance. In this project, a hybrid LSTM-GRU model is employed to leverage the unique strengths of both LSTM and GRU cells. This integration helps capture diverse temporal patterns and patient variability more effectively than individual models.
  2. **Problem Statement:**

Effective diabetes management requires precise insulin dosing, yet predicting short-acting insulin remains a complex task due to the dynamic and individualized nature of glucose-insulin interactions. These interactions are influenced by factors such as meal intake, physical activity, and individual metabolic responses. Clinical decision-making often relies on manual assessment, which may be inconsistent and time-consuming in resource-limited settings.This project aims to automate regular insulin dose prediction using deep learning models trained on the AIM94 dataset, which captures real-world clinical scenarios. By integrating a hybrid LSTM-GRU model alongside LSTM-Transformer and GRU-Transformer architectures, the approach enhances predictive accuracy and supports consistent, personalized insulin management.

* + 1. **Objectives**

1. **Integrate multi-source health data including blood glucose levels, insulin administration history, meal intake, physical activity, and special events, to create a comprehensive input feature set.**
2. **Develop an accurate insulin dosage prediction model using deep learning techniques that can effectively capture temporal and behavioral patterns in patient data.**
3. **Validate the performance of the proposed system using real-world data, ensuring its reliability and applicability in practical scenarios.**
   * 1. **Outcomes**
   1. A well-trained deep learning model capable of predicting optimal short-acting insulin doses by analyzing glucose levels, food intake, exercise activity, and other relevant clinical events.
   2. Improved patient outcomes through enhanced decision support, potentially reducing the frequency of hypoglycemia and hyperglycemia episodes by providing more consistent and personalized insulin recommendations.
   3. **Societal Impact of Proposed Work :**
   4. The automated insulin dose prediction model supports clinical decision-making by providing timely and personalized insulin recommendations, reducing the cognitive load on healthcare professionals.
   5. The use of interpretable deep learning models ensures transparency in predictions, enhancing clinician trust and enabling informed adjustments to patient treatment plans.
   6. Accurate and consistent insulin dosing helps minimize occurrences of hypoglycemia and hyperglycemia, leading to improved patient safety, better glycemic control, and enhanced long-term health outcomes.

**CHAPTER-2**

**REVIEW OF LITERATURE**

* 1. **Description of Existing Systems**
  2. **Summary of Literature Study**
  3. **Software Requirement Specification**

**CHAPTER-3**

**PROPOSED METHODOLOGY**

* 1. **Design Methodology**
  2. **System Architecture Diagram**
  3. **Description of Algorithms**
  4. **Description of datasets and Tools**