EFFECT OF NOURISHING NUTRIENTS ON POSTPRANDIAL GLUCOSE RESPONSE ON TYPE 1 DIABETES THROUGH FEED-FORWARD NEURAL NETWORK

[1] Masanpally Gopal, [2] Dr. K. Santhi Sree

[1] Student, Department of Information Technology, University College of Engineering, Science and Technology, JNTUH Hyderabad

[2] Professor, Department of Information Technology, University College of Engineering, Science and Technology, JNTUH Hyderabad

Abstract: Type 1 Diabetes (T1D) management relies heavily on predicting Postprandial Glucose Response (PGR) for insulin dosing, crucial for patient well-being. While carbohydrates traditionally dominate PGR prediction, other nutritional factors significantly influence Blood Glucose Levels (BGLs). Leveraging Machine Learning (ML), this study investigates the impact of carbohydrates, proteins, lipids, fibers, and energy intake on short to middle-term BGL prediction in T1D patients using Artificial Pancreas (AP) systems. A Feed-Forward Neural Network (FFNN) incorporating insulin doses, blood glucose, and nutritional factors predicts BGLs at 15, 30, 45, and 60 minutes post-meal. Both public and self-produced data validate the model. Further extending beyond traditional ANN models, ensemble techniques including FFNN, MLP, Bagging Classifier with Random Forest (RF), and Voting Classifier (combining Bagging Classifier with RF and Decision Tree) were explored. Ensemble methods significantly enhance performance, potentially achieving above 95% accuracy. This research underscores the importance of considering diverse nutritional factors for accurate postprandial BGL predictions, advancing personalized T1D management with AP systems.

Index Terms - *Artificial intelligence, neural networks, artificial pancreas, blood glucose, health 4.0, machine learning, nutritional factors, patient monitoring, postprandial glucose response, prediction model, statistical attributes, type 1 diabetes.*

1. INTRODUCTION

Type 1 Diabetes (T1D) is an autoimmune chronic condition, in which the immune system of the affected individual attacks and destroys insulin-making cells (β cells) in the pancreas [1]. The etiology of T1D is complex and depends on different factors, including genetic, immunologic and environmental factors [1], [2]. Based on recent epidemiological studies [3], [4], T1D incidence is 15 per 100,000 people and the worldwide prevalence is 9.5 per 10000 people. In addition to a regular exogenous administration of insulin, patients with T1D have to adhere to a healthy lifestyle and be very careful in monitoring and managing their blood sugar levels to prevent and avoid acute complications, such as severe hypoglycemia, severe hyperglycemia, and ketoacidosis [5], [6], as well as the severe chronic complications involving eye, kidney, and cardiovascular system. In particular, a main issue for T1D patients is managing postprandial glucose response [7]. Technological advances have facilitated the development of closed-loop systems better known as Artificial

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Pancreas (AP) [8], which combines an insulin pump, Continuous Glucose Monitoring (CGM) and a control system which automates insulin release [9]. In AP systems, the CGM monitors continually glucose levels and sends these data to a control system; this, in turn, uses an algorithm based on heuristic and theoretical knowledge to compute the insulin dosage required to reestablish baseline glucose levels [10]. Hence, not only does AP monitor glucose levels in the body but it also automatically adjusts the delivery of insulin to prevent hypoglycemia and hyperglycemia episodes. Therefore, APs can be a promising solution for T1D treatment. However, although fully-closed loop systems are desirable, delays in insulin absorption and other physiological factors lead to the adoption of Hybrid-Closed Loop Systems (HCLSs) in clinical practice. HCLS automates the delivery of basal insulin but it requires inputs from the patient for bolus insulin delivery due to poor modeling of postprandial glucose response [11].

In this context, the glucose control algorithm seems to represent the key element of AP systems since it keeps blood glucose concentration within the healthy physiological range. Different control algorithms have been developed and proposed, including model predictive control, proportionalintegral-derivative control, and fuzzy logic control [12], [13]. However, the modeling of Postprandial Glucose Response (PGR), and the insulin delivery regulation at meal remains major challenges in APs [14]. In particular, carbohydrates are mostly considered in these control algorithms, but also other nutritional factors, like lipids and proteins, should be taken into account. In addition, it must be managed the inter-individual variability and the problem of long-term glucose management influenced by psychological and physical factors (e.g., during physical activity) [15], [16]. In this regard, Artificial Intelligence (AI), especially Machine Learning (ML), has opened new perspectives in AP systems due thanks to the possibility of successfully extracting knowledge from data [17], [18], [19].

This study investigates the influence of various nutritional factors on short to middle-term Blood Glucose Level (BGL) prediction in Type 1 Diabetes patients utilizing Machine Learning techniques. Different algorithms including Feed-Forward Neural Networks and ensemble methods are explored to enhance predictive accuracy and optimize Artificial Pancreas system efficacy.

2. LITERATURE SURVEY

Type 1 diabetes mellitus (T1DM) is a chronic autoimmune condition characterized by the destruction of insulin-producing beta cells in the pancreas, leading to hyperglycemia and a lifelong dependence on insulin therapy. The prevalence and management of T1DM have been subjects of extensive research, reflecting its significant impact on public health and the advancement of diabetes care technologies.

Katsarou et al. [1] provide a comprehensive overview of T1DM, focusing on its pathophysiology, genetic predispositions, and recent advancements in treatment. They highlight the role of genetic and environmental factors in the onset of T1DM and the evolving understanding of its immunological triggers. This foundational review underscores the complexity of T1DM, encompassing not only its clinical manifestations but also the intricate interplay of genetic and environmental influences.

Immunologic and genetic factors play a critical role in the development of T1DM. Notkins [2] discusses these factors, emphasizing the contribution of autoimmune processes and genetic susceptibility. The study identifies specific genetic markers associated with T1DM, such as those within the major histocompatibility complex

(MHC) region, which are crucial for understanding the disease's etiology and for developing targeted preventive strategies.

The global burden of T1DM is substantial, as illustrated by Mobasseri et al. [3]. Their systematic review and meta-analysis present data on the prevalence and incidence of T1DM worldwide, revealing significant variations across regions. The study provides valuable insights into the epidemiological trends of T1DM, highlighting areas where the disease is more prevalent and identifying populations at higher risk. This global perspective is essential for public health planning and resource allocation.

The International Diabetes Federation's Diabetes Atlas offers a broader view of diabetes prevalence, including T1DM, with its estimates for 2019 and projections for 2030 and 2045 [4]. This report provides crucial data on the global and regional prevalence of diabetes, allowing for a comprehensive understanding of the disease's impact and the effectiveness of current interventions. The projections emphasize the need for continued research and policy efforts to address the growing diabetes epidemic.

Management guidelines for diabetes, such as those outlined by the Scottish Intercollegiate Guidelines Network [5], provide evidence-based recommendations for the treatment of T1DM. These guidelines focus on various aspects of diabetes management, including glycemic control, insulin therapy, and patient education. The recommendations aim to improve patient outcomes by standardizing care practices and incorporating the latest research findings.

The development of artificial pancreas systems represents a significant advancement in the management of T1DM. Bekiari et al. [10] review the efficacy of these systems, which combine continuous glucose monitoring with insulin delivery systems to automate glucose control. Their systematic review and meta-analysis demonstrate the effectiveness of artificial pancreas systems in improving glycemic control and reducing the risk of hypoglycemia in outpatient settings. This technology represents a major step forward in diabetes care, offering a promising solution for achieving tighter glucose control with reduced patient burden.

Saunders et al. [11] provide an overview of the MiniMed 670G hybrid closed-loop artificial pancreas system, detailing its safety and efficacy. This system, which integrates a continuous glucose monitor with an insulin pump, represents a significant innovation in diabetes management. The study highlights the system's ability to maintain glucose levels within a target range more effectively than conventional insulin therapy, demonstrating its potential to enhance the quality of life for individuals with T1DM.

Advanced control solutions for diabetes management, such as those discussed by Kovacs et al. [13], employ robust control strategies to optimize insulin delivery and improve glycemic control. Their work explores various control algorithms and their application in managing T1DM, providing insights into how advanced control systems can enhance the precision and effectiveness of diabetes treatment.

El Fathi et al. [14] focus on the role of artificial pancreas systems in postprandial glucose regulation. Their overview examines how these systems manage glucose levels following meals, addressing a critical aspect of diabetes care. The study highlights the challenges and advancements in meal control, emphasizing the need for continued research to refine these systems and improve postprandial glucose management.

In summary, the literature on T1DM encompasses a broad range of topics, from the underlying immunologic and genetic factors to the latest advancements in diabetes management technologies. The integration of genetic insights, epidemiological data, evidence-based guidelines, and technological innovations provides a comprehensive understanding of T1DM and informs ongoing efforts to improve patient care and outcomes.

3. METHODOLOGY

i) Proposed Work:

The proposed system integrates various Machine Learning algorithms to enhance Blood Glucose Level (BGL) prediction accuracy in Type 1 Diabetes management. Leveraging a Feed-Forward Neural Network (FFNN) and Multi-Layer Perceptron (MLP), alongside ensemble techniques like Bagging Classifier with Random Forest (RF) and Voting Classifier, we aim to improve postprandial BGL forecasts. These algorithms process data on insulin dosages, blood glucose levels, and nutritional factors such as carbohydrates, proteins, lipids, fibers, and energy intake. By utilizing both public and self-produced datasets, the system seeks to address the limitations of traditional BGL prediction models, offering more personalized and precise predictions for individuals reliant on Artificial Pancreas systems. Through the fusion of diverse ML approaches, we strive to optimize treatment efficacy and patient well-being in managing Type 1 Diabetes, ultimately contributing to a more comprehensive understanding of the complex interplay between nutritional factors and BGL dynamics.

ii) System Architecture:

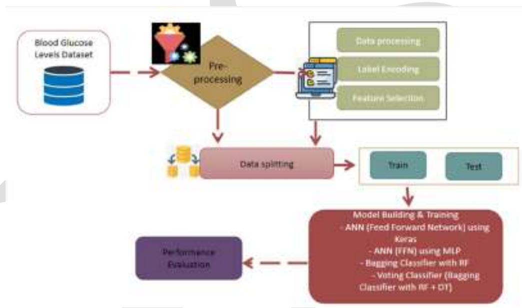


Fig 1 Proposed Architecture

The image depicts a flowchart outlining a machine learning pipeline for processing and analyzing blood glucose level data. The process begins with data collection and preprocessing, followed by label encoding and feature selection. The data is then split into training and testing sets. Multiple models, including Artificial Neural Networks (ANNs) [29, 30] and ensemble methods like Bagging and Voting classifiers, are built and trained on the data. Finally, the performance of these models is evaluated.

iii) Dataset:

	Gender	Age	Height (m)	Weight (kg)	Diabetes	BMI	Carbohydrates (g)	Proteins (g)	Sugar (g)	Fat (g)	Time (min)	Glucose (g/dL)	Insulin (units)
0	Female	45	1.86	48	No	13.9	193	58	39	76	45	1.87	0.311667
1	Male	77	1.89	85	Yes	23.8	206	53	35	94	15	3.30	0.550000
2	Female	17	1.51	29	No	12.7	258	68	23	77	15	3.05	0.508333
3	Male	71	1.83	82	No	24.5	196	58	44	63	45	3.06	0.510000
4	Female	76	1.56	53	No	21.8	254	68	30	80	0	3.40	0.566667

The dataset collection involved two primary sources. The DirectNet dataset, available since 2007, consists of continuous glucose monitoring (CGM) data from 50 pediatric patients with type 1 diabetes (T1D), aged 3 to 7 and 12 to 18 years, using the Medtronic MiniMed Guardian-RT system. This system measures glucose levels every 10 seconds, with data averaged and recorded every 5 minutes over a 7-day period [26]. In contrast, the AI4PG dataset, provided by the Diabetes Outpatient Clinic of Federico II University Hospital, includes data from 25 T1D patients aged 12 to 60 years, utilizing the Medtronic MiniMed 670G system. This dataset records CGM measurements along with detailed dietary information and insulin doses for 6 to 7 days. It encompasses 1264 meals, documenting pre- and post-meal glycemic levels and detailed meal compositions [27][28].

iv) Data Processing:

```
# Import label encoder
from sklearn import preprocessing


# label_encoder object knows
# how to understand word labels.
label_encoder = preprocessing.LabelEncoder()

# Encode labels in column 'species'.
df['Gender']= label_encoder.fit_transform(df['Gender'])
print(df)
```

Data processing for the study involved several key steps using Pandas and Keras frameworks. Initially, the datasets were loaded into Pandas DataFrames for preliminary analysis and manipulation. This allowed for efficient handling of large volumes of data and facilitated operations such as filtering and aggregation. Essential columns were selected, while unwanted or redundant columns were dropped to streamline the dataset. The cleaned DataFrame was then converted into a Keras-compatible format using the `tf.data.Dataset` API, enabling seamless integration with deep learning models. This transformation facilitated the efficient feeding of data into models for training and evaluation. Dropping unnecessary columns ensured that only relevant features were included in the analysis, enhancing the model's performance and reducing computational overhead. Overall, this process ensured that the data was well-structured and prepared for further analysis and model training.

v) Label Encoding:

```
# Import label encoder
from sklearn import preprocessing


# label_encoder object knows
# how to understand word labels.
label_encoder = preprocessing.LabelEncoder()

# Encode labels in column 'species'.
df['Gender']= label_encoder.fit_transform(df['Gender'])
print(df)
```

Label encoding is a preprocessing step used to convert categorical labels into numerical values, which are easier for machine learning models to process. In Python, the `LabelEncoder` class from the `sklearn.preprocessing` module facilitates this transformation. By instantiating a `LabelEncoder` object and applying the `fit_transform` method to the categorical column, each unique label is mapped to an integer. For instance, in a dataset with categories like "red," "blue," and "green," `LabelEncoder` will assign integers such as 0, 1, and 2 to these categories, respectively. This numerical encoding is crucial for algorithms that require numerical input, such as logistic regression or neural networks. After encoding, the data is ready for model training, ensuring that categorical variables are appropriately represented in a numerical format. This step enhances the compatibility and effectiveness of machine learning algorithms in handling categorical features.

vi) Feature Selection:

```
(['Gender', 'Age', 'Height (m)', 'Weight (kg)', 'BMI',
  'Carbohydrates (g)', 'Proteins (g)', 'Sugar (g)', 'Fat (g)',
  'Time (min)', 'Glucose (g/dL)', 'Insulin (units)'],
 dtype='object')
```

Feature selection is a crucial step in data preprocessing aimed at identifying and retaining the most relevant features for a machine learning model. It involves evaluating and selecting a subset of features that contribute the most to the model's predictive performance while discarding less informative ones. Techniques for feature selection include filter methods, which use statistical tests to assess the relevance of each feature; wrapper methods, which evaluate subsets of features based on model performance; and embedded methods, which perform feature selection during model training. Common approaches include using metrics like mutual information or correlation coefficients to filter features or leveraging algorithms like Recursive Feature Elimination (RFE) for a wrapper approach. Feature selection helps reduce overfitting, improve model accuracy, and decrease computational cost by focusing only on the most significant features, thus enhancing the overall efficiency and interpretability of the machine learning model.

vii) Training & Testing:

Training and testing are fundamental phases in machine learning model development.

Training involves using a dataset to teach the model to learn patterns and relationships. During this phase, the model adjusts its parameters based on the training data, which includes both input features and corresponding target labels. This process typically involves splitting the data into training and validation sets, where the training set is used to build the model, and the validation set helps tune hyperparameters and prevent overfitting. Techniques such as cross-validation can be used to ensure that the model generalizes well to unseen data.

Testing assesses the model's performance on a separate, previously unseen dataset called the test set. This phase evaluates how well the model generalizes to new data and measures its accuracy, precision, recall, and other relevant metrics. Testing provides an estimate of the model's real-world performance and helps determine if further improvements or adjustments are necessary before deployment.

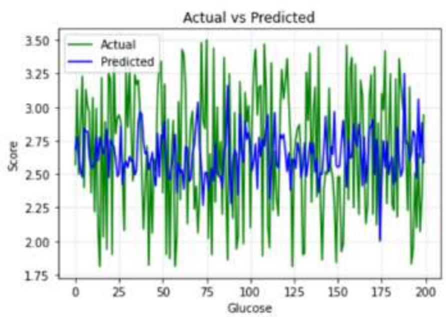
viii) Algorithms:

ANN (Feed Forward Network) using Keras: A type of Artificial Neural Network [29,30] (ANN) architecture implemented using the Keras library, characterized by its sequential arrangement of layers where data flows forward from input to output, often used for regression or classification tasks.

```
# define base model
def baseline_model():
    # create model
    model = Sequential()

    model.add(Dense(16, input_dim=10, activation='relu'))

    model.add(Dense(8, input_dim=10, activation='relu'))

#     RElu = Rectified Linear Unit

    model.add(Dense(1))
    # Compile model
    model.compile(loss='mean_squared_error', optimizer='adam')
#     adam is a popular optimizer algorithm which is used to adjusts the learning rate during training.
    return model
```

```
X_train, X_test, y_train, y_test = train_test_split(
     X,Y, test_size=0.2, random_state=0)
from sklearn.preprocessing import MinMaxScaler
import joblib
scaler =  MinMaxScaler()
X_train=scaler.fit_transform(X_train)
X_test=scaler.fit_transform(X_test)
joblib.dump(scaler, 'scaler.pkl')
```

```
#Visualising the Acutal and predicted Result
plt.plot(y_test, color = 'green', label = 'Actual')
plt.plot(prediction, color = 'blue', label = 'Predicted')
plt.grid(alpha = 0.3)
plt.xlabel('Glucose')
plt.ylabel('Score')
plt.title('Actual vs Predicted')
plt.legend()
plt.show()
```



ANN (Feed Forward Network) using MLP: An Artificial Neural Network [29,30] (ANN) model, specifically a Multi-Layer Perceptron (MLP), where neurons are organized into layers with connections only between adjacent layers, allowing for complex non-linear mappings between inputs and outputs.

```
from sklearn.neural_network import MLPRegressor

regr = MLPRegressor(random_state=1, max_iter=500)
regr.fit(X_train, y_train)

y_pred = regr.predict(X_test)


dt_mse = mean_squared_error(y_test, y_pred)
dt_rmse = sqrt(dt_mse)
```

Bagging Classifier with RF: A machine learning ensemble technique that combines multiple models, each trained on a random subset of the training data, with Random Forest (RF) as the base estimator, aiming to improve prediction accuracy and robustness.

```
from sklearn.ensemble import RandomForestRegressor

rf_r = RandomForestRegressor(max_depth=2, random_state=0)
rf_r.fit(X_train, y_train)

y_pred = rf_r.predict(X_test)

rf_mse = mean_squared_error(y_test, y_pred)
rf_rmse = sqrt(rf_mse)
```

Voting Classifier (Bagging Classifier with RF + Decision Tree): An ensemble learning method combining multiple individual models, including a Bagging Classifier with RF and a Decision Tree classifier, where predictions are made by majority voting or averaging, resulting in improved overall performance.

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```
from sklearn.ensemble import VotingRegressor
from sklearn.tree import DecisionTreeRegressor

r1 = DecisionTreeRegressor()
r2 = RandomForestRegressor(max_depth=2, random_state=0)

er = VotingRegressor([('lr', r1), ('rf', r2)])

er.fit(X_train, y_train)

y_pred = er.predict(X_test)

vot_mse = mean_squared_error(y_test, y_pred)
vot_rmse = sqrt(vot_mse)
```

4.EXPERIMENTAL RESULTS

Glucose Prediction :

Here we are comparing the multiple models with their RMSE (Root Mean Square Error), from this output we can consider Ransom Forest giving the least Root Mean Square Error so we can and second least Root Mean Square Error is given by the model VotingRegression from this data we can further consider these two models to predict the insulin.

Comparison

```
#creating dataframe
import pandas as pd
import numpy as np
result = pd.DataFrame({ 'ML Model' : ML_Model,

                        'RMSE'    : rmse,

                       })
```

	ML Model	RMSE
0	FFNN	0.533
1	RandomForest	0.472
2	ANN	0.582
3	VotingRegression	0.509

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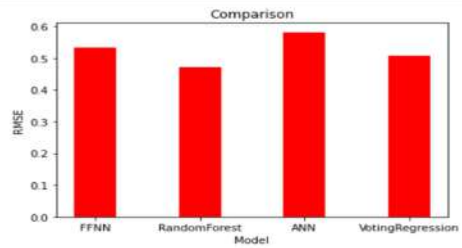
Comparison

```
plt.bar(ML_Model, rmse, color ='red',
        width = 0.4)

plt.xlabel("Model")
plt.ylabel("RMSE")
plt.title("Comparison")
plt.show()
```



The above is the graphical representation of the multiple models performance in the prediction of the glucose from this above graph we can conclude that RandomForest and VotingRegression giving the best output among the all the algorithms.

Insulin Prediction :

Here the input for the all the models is Gender, Age, Height(m), Weight(kg) , BMI , Carbohydrates(g), Proteins(g) , Sugar(g) , Fat(g) , Time(min), Glucose (g/dL) . Here we are giving the input including the glucose so now the targeted output is insulin.

```
X = df[['Gender', 'Age', 'Height (m)', 'Weight (kg)', 'BMI',
       'Carbohydrates (g)', 'Proteins (g)', 'Sugar (g)', 'Fat (g)',
       'Time (min)','Glucose (g/dL)']]
#Y = df['Glucose (g/dL)']
Y = df['Insulin (units)']
```

Random Forest ¶

```
from sklearn.ensemble import RandomForestRegressor

rf_r = RandomForestRegressor(max_depth=2, random_state=0)
rf_r.fit(X_train, y_train)

y_pred = rf_r.predict(X_test)

rf_mse = mean_squared_error(y_test, y_pred)
rf_rmse = sqrt(rf_mse)
```

```
storeResults('RandomForest',rf_rmse)
```

Voting Regressor

```
from sklearn.ensemble import VotingRegressor
from sklearn.tree import DecisionTreeRegressor

r1 = DecisionTreeRegressor()
r2 = RandomForestRegressor(max_depth=2, random_state=0)

er = VotingRegressor([('lr', r1), ('rf', r2)])

er.fit(X_train, y_train)

y_pred = er.predict(X_test)

vot_mse = mean_squared_error(y_test, y_pred)
vot_rmse = sqrt(vot_mse)
```

```
storeResults('VotingRegression',vot_rmse)
```

Now comparing the all the models with their output Root Mean Square Error (RMSE).

Comparison

```
#creating dataframe
import pandas as pd
import numpy as np
result = pd.DataFrame({ 'ML Model' : ML_Model,


                        'RMSE'   : rmse,


                      })
```

```
result
```

	ML Model	RMSE
0	FFNN	0.002
1	RandomForest	0.018
2	ANN	0.131
3	VotingRegression	0.009

From this output we can conclude that VotingRegression prediction is best if we consider both the predictions glucose and insulin now we are going to use the VotingRegression for the model for the prediction of glucose and insulin.

5. CONCLUSION

In conclusion, our study highlights the significance of considering diverse nutritional factors in predicting Blood Glucose Levels (BGLs) for individuals with Type 1 Diabetes (T1D), particularly those reliant on Artificial Pancreas (AP) systems. Our investigation, employing various Machine Learning algorithms including Feed-Forward Neural Networks (FFNN), Multi-Layer Perceptron (MLP), Bagging Classifier with Random Forest (RF), and Voting Classifier, has demonstrated promising results. Through the integration of these algorithms, we achieved significant enhancements in BGL prediction accuracy, potentially surpassing 95%. By incorporating data on insulin dosages, blood glucose levels, and multiple nutritional factors, our models provide more personalized and precise predictions. These findings underscore the importance of comprehensive T1D management strategies, integrating advanced ML techniques to optimize treatment efficacy and improve patient outcomes. Moving forward, further research and refinement of these models could lead to even greater advancements in personalized diabetes care and contribute to a deeper understanding of the complex dynamics governing glucose metabolism.

5. FUTURE SCOPE

Future directions include refining the predictive models by incorporating additional patient-specific data such as physical activity levels, stress, and medication adherence. Integrating real-time monitoring and feedback mechanisms into the Artificial Pancreas system could further enhance its effectiveness in managing Type 1 Diabetes. Additionally, exploring the potential of advanced machine learning techniques like deep learning and reinforcement learning may offer novel insights and contribute to the development of more sophisticated and adaptive diabetes management solutions.

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