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**BLOOD GLUCOSE LEVEL PREDICTION MODEL
USING NON-CLINICAL DATA FOR TYPE 2
DIABETIC PATIENTS IN SRI LANKA**

B.L.K.A.Balasooriya

178076N

Master of Philosophy (MPhil)

Department of Electronic and Telecommunication Engineering
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Dissertation submitted in partial fulfillment of the requirements for the
degree

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DECLARATION

I declare that this is my own work and this Dissertation does not incorporate without acknowledgement any material previously submitted for a Degree or Diploma in any other University or Institute of higher learning and to the best of my knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgement is made in the text. I retain the right to use this content in whole or part in future works (such as articles or books).

Signature:

Date: 21/10/2025

The supervisors should certify the Dissertation with the following declaration.

The above candidate has carried out research for the Master of Philosophy (MPhil) Dissertation under our supervision. We confirm that the declaration made above by the student is true and correct.

Name of Supervisor: Dr. Rukshani Liyanaarachchi

Signature of the Supervisor:

Date: 21/10/2025

Name of Supervisor: Dr. N. W. Nuwan Dayananda

Signature of the Supervisor:

Date: 21/10/2025

DEDICATION

I would like to dedicate this work to my supervisors, whose expertise and guidance have been instrumental in shaping my research skills and knowledge. Their mentorship has been invaluable for my academic and professional growth.

This research project is dedicated to my family members, whose unwavering love and support have been the driving force behind my academic pursuits. Their encouragements and beliefs in me have been an inspiration and I am forever grateful for their guidance.

Finally, I would like to dedicate this research to all those who have been affected by the subject matter of this study. It is my hope that this research will contribute to the advancement of knowledge and understanding in this field and lead to positive change and progress.

Thank you for your support and encouragement to this research.

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ABSTRACT

Diabetes is a chronic disease characterized by elevated blood glucose levels. Poorly managed diabetes can cause serious complications when blood sugar levels consistently exceed clinically acceptable ranges. Knowing the variations in blood glucose levels allows active participation in maintaining blood glucose levels of patients with diabetes within clinically acceptable limits. Effective management of blood glucose prevents serious complications. Early information on glucose changes helps diabetes patients manage their dietary plans, medication doses, and lifestyle. Frequent or regular blood glucose monitoring can be challenging, as standard blood glucose meters require a small blood sample from a fingertip to measure glucose levels in patients with type 2 diabetes. These measurements are obtained after the patient's blood glucose levels have already changed.

Continuous Glucose Monitoring (CGM) devices offer an alternative for diabetic patients to monitor their blood glucose levels. These devices use a tiny sensor implanted under the patient's skin. Most existing techniques leverage recorded CGM measurements, insulin doses, and dietary intake of diabetic patients to predict blood glucose levels at 30 min, 60 min, and 75 min intervals in the future. Diabetic patients must be aware of their daily routines and meals to manage their blood glucose levels, which can be controlled using correct dosages. A personalized self-management tool, such as a mobile application, can help patients collect data accurately. CGM devices are usually used in type 1 diabetic patients integrated with insulin pumps. There is an additional risk if an implanted CGM is used in patients with type 2 diabetes. This study introduces a machine learning algorithm that uses input data, including current glucose levels and previously predicted, medication dosage, food consumption, and physical activity of type 2 diabetic patients for short-term prediction of blood glucose level. A long-short-term memory model (LSTM) was developed to forecast blood glucose levels in type 2 diabetic patients at 30 min and 60 min intervals. Two methods were used to collect blood glucose data from diabetic patients for model development: continuous data from 10 subjects over 7 days and random data from 100 subjects over a few hours. The prediction model demonstrated an improved accuracy for the prediction of 30 min and 60 min. The root mean square error of this model at 30 min and 60 min was 18.8 mg/dl and 20.3 mg/dl, respectively, with accuracies of 81.49% and 79.86%. Furthermore, the prediction data in the LSTM model fell within the clinically acceptable "A" zone of the Clark Error Grid. Most previous models predicted blood glucose values for type 1 diabetic patients using various physiological parameters. This study predicted blood glucose levels in type 2 diabetic patients using a minimal training dataset. The accuracy of the model to predict blood glucose levels in type 2 diabetic patients can be improved by training it with a larger data set from a more extensive patient population.

Keywords: Diabetes, prediction model, Time series prediction, Physical parameters

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