How do ML techniques compare in accuracy and reliability for predicting Type 2 Diabetes Mellitus (T2DM) risk to DL Methods, and in what ways can a hybrid approach improve prediction outcomes across populations?

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INTRODUCTION

- T2DM is a chronic disease with a significant impact on global health.
- Early prediction is crucial for preventive measures and management.
- Traditional ML and DL methods have yet to be fully compared in this context.
- A novel hybrid approach combining ML and DL could potentially offer superior predictions.
- Aiming to enhance early detection and management of T2DM.

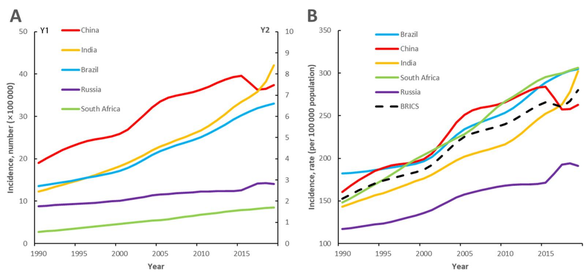


Fig 1: Number new of T2DM, and incidence rate of T2DM across Brazil, China, India, Russian Federation, and South Africa between 1990 and 2019

METHODS

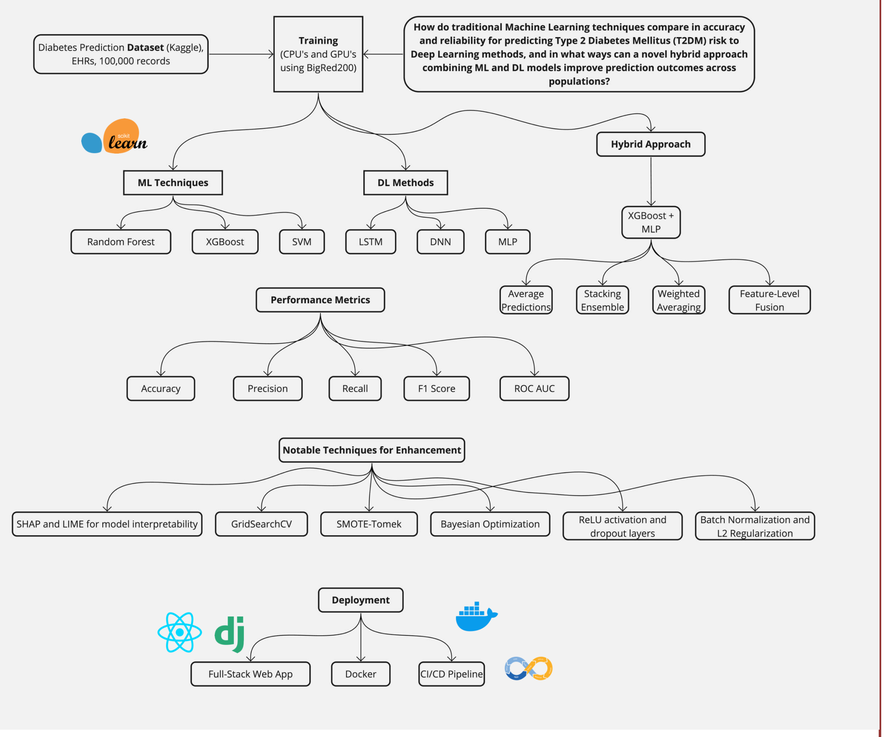


Fig 2: A comprehensive flowchart of some methods used throughout the research

CONCLUSIONS

- Tools like LIME and SHAP were instrumental in interpreting the models, providing insights into feature contributions and enhancing trust in the model predictions
- Hybrid modeling techniques, including averaging predictions, stacking, and weighted averaging, proved to be effective in combining model strengths and mitigating individual weaknesses.
- There is an opportunity for future research to explore the integration of these models into real-world clinical workflows and to validate their performance on larger, more diverse datasets.

RESULTS

Data Preprocessing and Initial Analysis

Fig 3: Correlation Matrix of Numerical Features and Diabetes

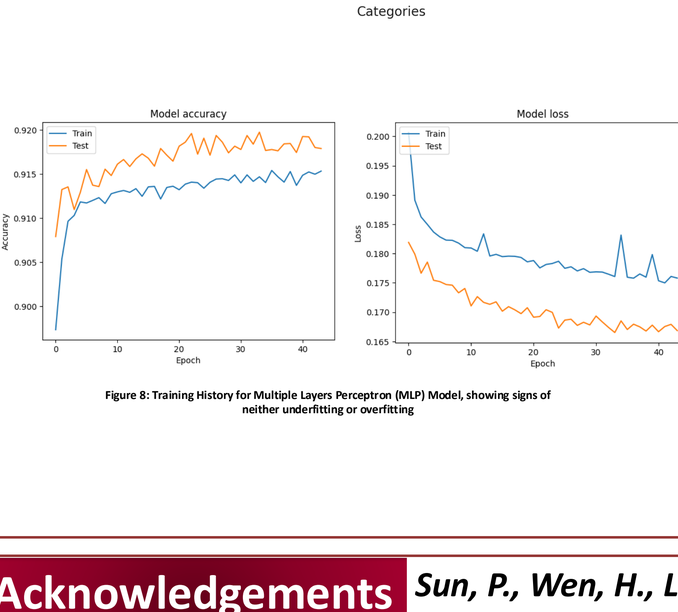


Figure 4: Class Distribution Before and After Outlier Removal

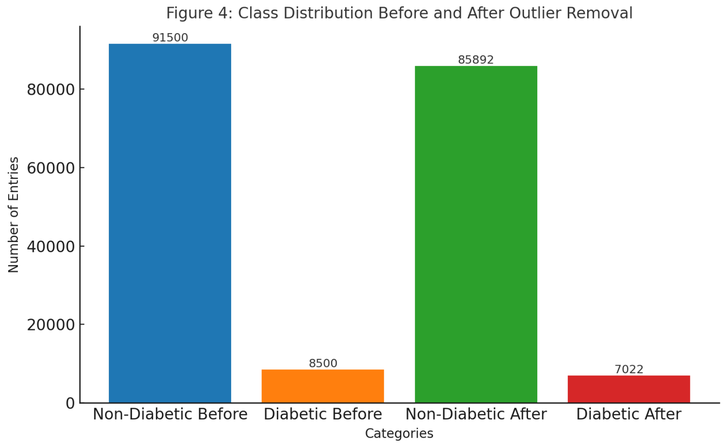


Figure 8: Training History for Multiple Layers Perceptron (MLP) Model, showing signs of neither underfitting or overfitting

Model Performance Comparison

Figure 5: Machine Learning Model Performance Comparison

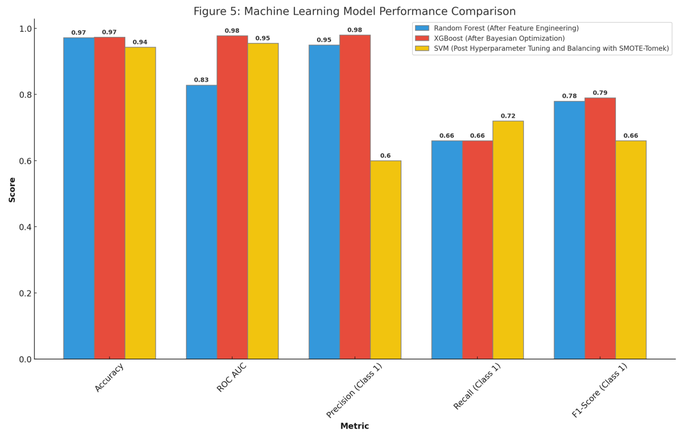
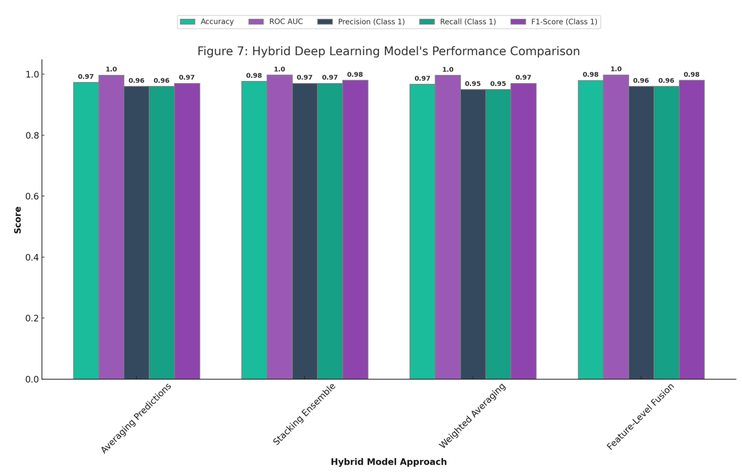


Figure 6: Deep Learning Model's Performance Comparison

Figure 7: Hybrid Deep Learning Model's Performance Comparison



Model Interpretability and Explainability

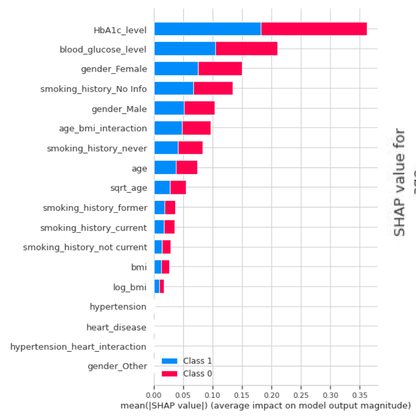


Figure 9: Feature Importance Analysis for Diabetes Prediction using SHAP Values (Random Forest)

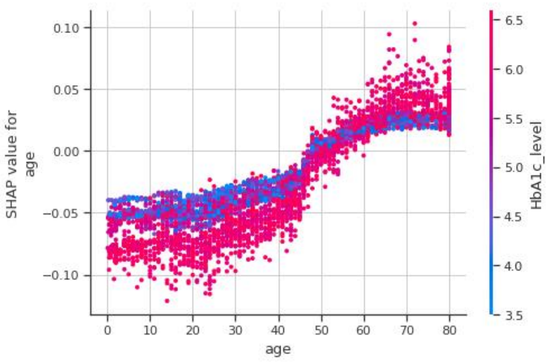


Figure 10: SHAP Value Dependence Plot for Age Feature Relative to HbA1c Level in Diabetes Prediction (Random Forest)

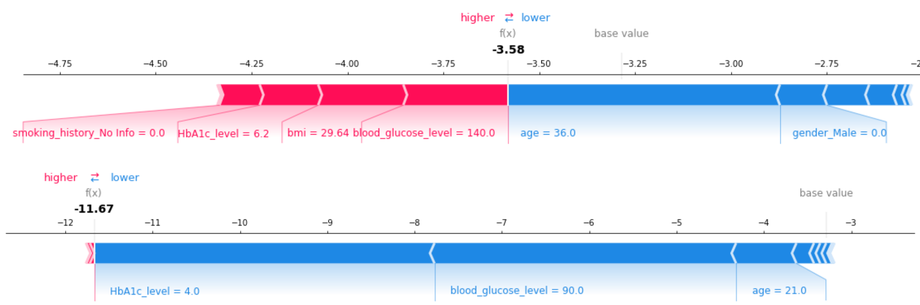


Figure 11: SHAP Force Plot Illustrating Individual Feature Contributions to Diabetes Prediction Model (XGBoost)

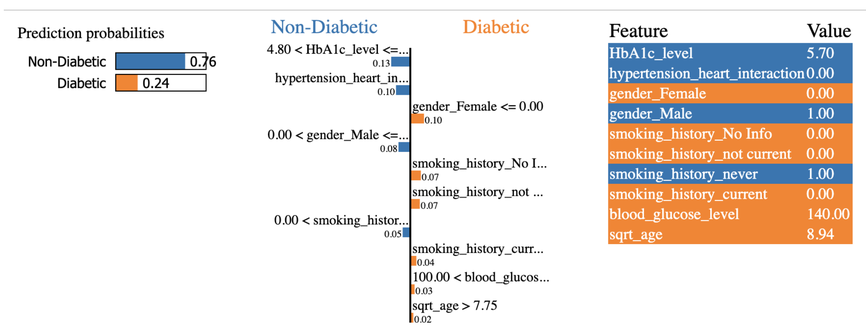


Figure 12: LIME Explanation Visualization for a Diabetes Prediction Model (Random Forest)

GitHub Repository

Acknowledgements and References

Sun, P., Wen, H., Liu, X. et al. Time trends in type 2 diabetes mellitus incidence across the BRICS from 1990 to 2019: an age-period-cohort analysis. BMC Public Health 22, 65 (2022). https://doi.org/10.1186/s12889-021-12485-y

I would also like to thank William Reindl and Nikhil Dhoka for partially helping me with this project during the 2-day Purdue Boilermake Hackathon