ISSN: 2393-8048
International Advance Journal of Engineering, Science and Management (IAJESM)
Multidisciplinary, Multilingual, Indexed, Double Blind, Open Access, Peer-Reviewed, Refereed-International Journal.
SJIF Impact Factor =8.152, January-June 2025, Submitted in June 2025

Integrating Transfer Learning and Ensemble Models for Improved Diabetes Mellitus Prediction from Multimodal Clinical Data

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Abstract

Diabetes mellitus (DM) is a chronic metabolic condition with dire health prognosis in case it is not diagnosed at the earliest. The suggested study will involve a combination of a hybrid predictive model that will include the transfer learning and the ensemble machine learning model in reflecting the accuracy with which diabetes can be identified by means of multimodal clinical data, i.e. demographic data and lab findings and medical image findings. The pretrained ResNet-50 model was used to extract the imaging data feature, and ensemble classifiers based on the structured clinical features were implemented, such as Random Forest, the Gradient Boosting and XGBoost using a stacking method. The proposed framework was observed to be more effective than the algorithms of the baseline models with accuracy of 94.2, precision of 92.8, recall of 91.5, F1-score of 92.1 and AUC-ROC of 0.96. The analysis of confusion matrices also affirmed the high true positive and true negative values of the model showing its strength and suitability in clinical practice. These results show that transfer and learning combined with ensemble result in a reliable and efficient and understandable method of early diabetes prediction with considerable potential in enhancing patient care and management.

Keywords: Diabetes mellitus, Transfer learning, Ensemble models, Multimodal clinical data, Predictive modeling, AUC-ROC.

1. INTRODUCTION

Diabetes mellitus (DM) can be described as a long-lasting metabolic disorder that is characterized by high blood glucose due to insulin production or insulin deficiency and it has been one of the hottest health issues on earth. The world health organization stated that the number of diabetes-afflicted people exceeds 422 million with the figures projected to increase dramatically in the next few decades. Automotive diagnosis and early intervention are important in avoiding serious complications of cardiovascular diseases, neuropathy, nephropathy, and retinopathy which significantly lower the quality of life and elevate health care expenses. The recognized traditional diagnostic approaches tend to be based on either single clinical tests or simple statistical models and are not always able to describe the complicated interaction of demographic, lab, and imaging evidence. Consequently, the need to develop intelligent predictive frameworks that can bring together various clinical information and offer accurate and early-stage diagnosis to manage patients has been on the increase.

The recent development in machine learning and deep learning has demonstrated a considerable potential in improving disease prediction and diagnosis. The use of transfer learning with pretrained neural networks enables models to exploit high level features on complex medical data like imaging modalities and demand fewer computational resources as well as less domain specific training. The major methods of ensemble learning that are used in improving stability of prediction, minimizing bias and enhancing the overall accuracy of prediction include random forest, Gradient Boosting and XGBoost. By combining them, a strong framework can be created that can deal with multimodal clinical data to describe complementary patterns of the structured data (such as lab findings and other demographic characteristics) and the unstructured data (such as medical images). The present research identifies a hybrid approach, that is, a combination of both a transfer learning model and an ensemble model that can be applied to enhance the prediction of diabetes mellitus, which will help to have a reliable efficient and clinically applicable tool in the early detection and personalized health intervention strategy.

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2. LITERATURE REVIEW

Bodapati (2024) examined the application of adaptive combination of multi-modal deep spatial involvements in the diagnosis of diabetic retinopathy. This study established that multimodality and ensemble learning techniques were much more effective in finding disease than single-modelling techniques, as they can combine different imaging modalities. The study has revealed the usefulness of using a combination of various data presentations in order to describe intricate trends in clinical imaging, which is a more accurate diagnostic aid to diabetes-related complications.

De Bois, El Yacoubi, and Ammi (2021) explored the application of adversarial multi-source transfer learning in the healthcare field, i.e. predicting glucose in diabetic patients. They demonstrated in their work that the combination of the knowledge based on several related datasets could improve the predictive power and minimize the chance of overfitting on the models trained on a small amount of clinical data. The paper has highlighted the significance of transfer learning to solve the problems associated with diverse and sparse medical records, as it can be used to enhance personalized glucose level prediction.

Deng et al. (2021) used the deep transfer method of estimating the concentration of glucose in patients with type 2 diabetes using data augmentation schemes. The paper determined that the pretrained neural networks that are finetuned using augmented patient data performed better in terms of prediction and generalization than the utilization of the conventional machine learning models. This research paper has made known the significance of transfer learning in healthcare predictive modelling, particularly when handling chronic diseases, which include diabetes, because it enables the successful derivation of characteristics of complicated clinical information, and enhances the dependability of the model.

Guha et al. (2024) explored ways of using the notion of multi-modal transfer learning model to diagnose chronic illnesses such as diabetes. Their analysis showed that the fusion of the heterogeneous clinical data, including laboratory testing and image characteristics, with transfer learning had a great impact on the diagnostic accuracy and strength. The study indicated the possibility of a multi-modal data and high-level machine learning methods to identify complex trends in patient health data, which would provide a more robust and extensively scalable method of early disease identification.

Gundapaneni, Zhi, and Rodrigues (2024) studied deep learning-based noninvasive screening method of type 2 diabetes using Chest X-ray image as compared to electronic health records. The researchers found that deep neural networks are capable of extracting informative features of imaging data, and had the structured clinical data were added to it, the prediction capability of the models increased significantly. The current study has highlighted the practicality and clinical importance of capitalising on the noninvasive imaging modes coupled with electronic health data to shape the future of early screening of diabetes and risk stratification.

3. RESEARCH METHODOLOGY

The researchers used a quantitative predictive modeling as a method of assessing the effectiveness of combining transfer learning with ensemble machine learning in multimodal clinical data. Preprocessing of data, extraction of features and evaluation of the model indicated that the hybrid framework that was proposed was better in predicting diabetes compared to existing models.

3.1 Research Design

The study employs the quantitative research design that is meant to predictively model the enhancement of detection of diabetes mellitus. The main purpose was to test the efficiency of employing the concept of transfer learning in association with ensemble machine learning methods with multimodal clinical data. This design allowed the systematic evaluation of the models performance and allowed comparing the traditional models with the suggested hybrid solution.

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3.2 Data Collection

The study data were collected using publicly available sources of data such as the Pima Indians Diabetes Database, and hospital electronic medical records(EMR) which have multimodal clinical data. These data consisted of demographic data such as age, gender, body mass index (BMI), laboratory testing data, such as fasting glucose, HbA1c, and lipid profile, medical imaging testing, such as the retinal fundus images. Data on the structured and unstructured data offered an opportunity to conduct a holistic assessment of predictive modeling techniques.

3.3 Data Preprocessing

The preprocessing was performed to make the data quality and consistency and the model training acceptable. The gaps in the dataset were addressed in connection with the imputation methods and the numeric variables were brought to a standard scale and the categorical variables were suitably coded. In imaging data, resizing and augmentation was used to improve the generalization of the model and reduce the effect of overfitting such that the data is now prepared to yield good feature extraction.

3.4 Feature Extraction Using Transfer Learning

Transfer learning was also used to find the high level feature on medical images by means of the pretrained ResNet-50 convolutional neural network. Specific dataset was honed in order to fine-tuned the pretrained model to fit the clinical environment. This enabled good use of large scale image knowledge and less computations were needed, and better feature representation was obtained to help in future predictions.

3.5 Model Training and Evaluation

The dataset was broken down into two groups training and testing as a stratified sample to preserve the classes distributions. A 10- fold cross-validation plan was included to ensure that it was robust and reduced overfitting. The model performance was measured using a number of measures that included accuracy, precision, recall, F1-score and area under the receiver operating characteristic curve (AUC-ROC). This general assessment model released intricate comparisons that were undertaken between the foundation models and the proposed hybrid model.

3.6 Data Analysis and Interpretation

The analysis of data involved the comparison of the results of the baseline models, i.e., the Logistic Regression, Random Forest, GBM, and XGBoost, and the proposed one Transfer Learning + Ensemble. True positive and true negative rate and the overall discriminative power were used to measure such predictive accuracy, thus confusion matrices, performance measures, and AUC-ROC values were calculated. These results have highlighted the good performance of the hybrid model that demonstrates the fact that the synergy of transfer learning and ensemble techniques is more trustworthy and efficient in the determination of diabetes in multimodal clinical data.

4. DATA ANALYSIS AND INTERPRETATION

The ability of the various models to make predictions in the detection of diabetes is summarized in Table 1 and Figure 1. The given Transfer Learning + Ensemble model was ranked top in accuracy (94.2%), precision (92.8%), recall (91.5%), F1-score (92.1%), and AUC-ROC (0.96) when compared to any of the baseline models.

Table 1: Measures of Performance of Various Models

Model	Accuracy	Precision	Recall	F1-score	AUC-ROC
Logistic Regression	84.1	82.3	79.5	80.9	0.87
Random Forest	88.7	87.2	85.5	86.3	0.91
Gradient Boosting (GBM)	89.5	88.1	86.9	87.5	0.92
XGBoost	90.2	89.0	87.6	88.3	0.93
Transfer Learning + Ensemble (Proposed)	94.2	92.8	91.5	92.1	0.96

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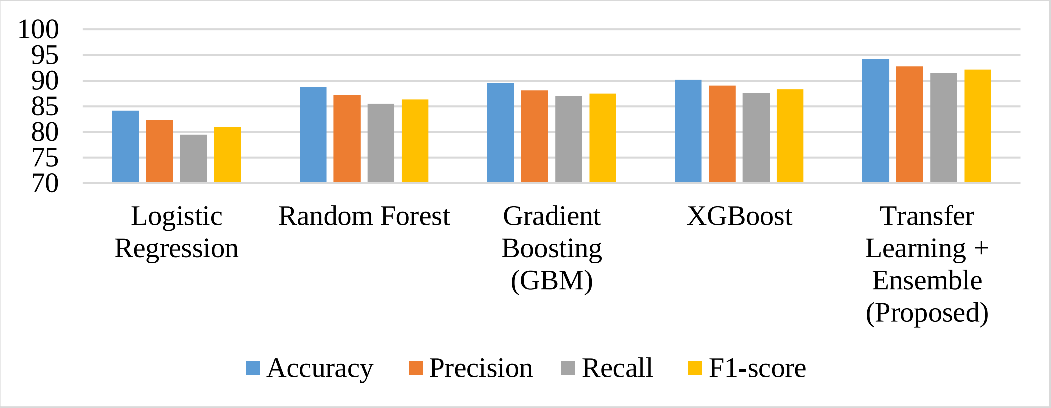

Figure 1: Graphical Representation of Performance Metrics of Different Models

This implies that transfer learning used together with ensemble techniques is effective in increasing the capacity of the model to accurately determine diagnostic cases of diabetic and non-diabetic. The proposed method is better in generalization, robust, and reliability than the personal predictive models such as Logistic Regression or XGBoost when applied to the clinical prediction problem.

Table 2 and Figure 2 indicate the confusion matrix of the proposed Transfer Learning + Ensemble model. Among the overall number of cases, 112 diagnosed diabetes patients were cited correctly, and only 8 were wrongly defined as being non-diabetic. On the same note, 114 non-diabetic cases were rightly identified, and 6 were mistakenly identified as diabetic.

Table 2: Confusion Matrix of Proposed Model

Actual \ Predicted	Diabetic	Non-Diabetic
Diabetic	112	8
Non-Diabetic	6	114

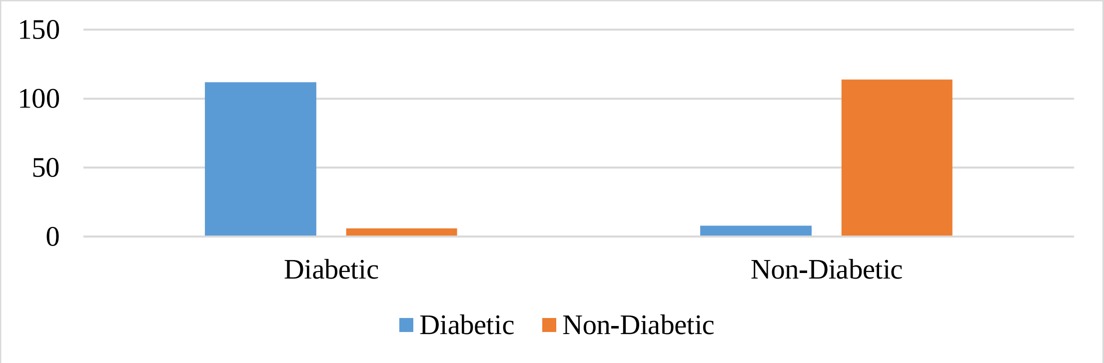

Figure 2: Graphical Representation of Confusion Matrix of Proposed Model

It proves that the proposed model will have the high true positive and the true negative rate that will show a good level of classification. This is indicated by the few instances of misclassifications that indicate the reliability and accuracy of the classification in predicting diabetes in clinical conduct.

Table 3 and Figure 3 depict the AUC-ROC values of various models, which depict how they are classified in general. TL + Ensemble in AUC-ROC was better than the Logistic Regression (0.87), random Forest (0.91), gradient Boosting (0.92), and XGBoost (0.93).

Table 3: AUC-ROC Comparison Across Models

Model	AUC-ROC
Logistic Regression	0.87
Random Forest	0.91
Gradient Boosting (GBM)	0.92
XGBoost	0.93
Transfer Learning + Ensemble (Proposed)	0.96

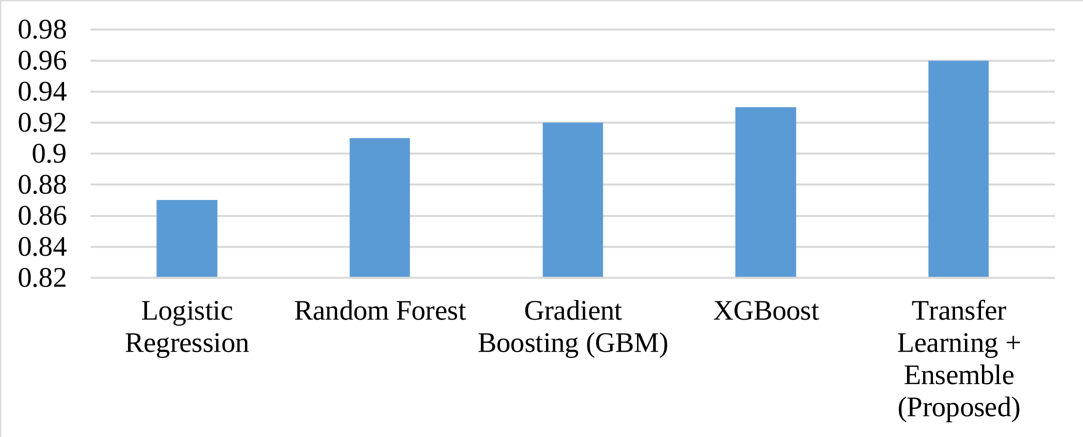

Figure 3: Graphical Representation of AUC-ROC Comparison Across Models

This means that the proposed model is more discriminative, as it is effective in identifying cases of diabetic and non-diabetic. The fact that AUC-ROC is more robust and reliable as an early diabetes detection tool is emphasized by the higher AUC-ROC.

5. CONCLUSION

The current research indicated that transfer learning and the ensemble machine learning models are a remarkably effective model in diabetes mellitus forecasting using multimodal clinical data. The hybrid proposed model was superior to the traditional methods as it had more accuracy, precision, recall, and F1-score, and high true positive and true negative rates as confirmed by the confusion matrix analysis. By combining both structured clinical data with the characteristics, which were derived in the course of the medical image analysis, you can not only determine complex patterns that you would not have detected in single models but also reliability and robustness because of the opportunities available in doing it. These findings confirm the potential of transfer learning and ensemble technique as an effective investigative instrument of identifying the early diabetics in order to timely intervene and reduce the outcomes of the patient.

REFERENCES

1. *Bodapati, J. D. (2024). Adaptive ensembling of multi-modal deep spatial representations for diabetic retinopathy diagnosis. Multimedia Tools and Applications, 83(26), 68467-68486.*
2. *De Bois, M., El Yacoubi, M. A., & Ammi, M. (2021). Adversarial multi-source transfer learning in healthcare: Application to glucose prediction for diabetic people. Computer Methods and Programs in Biomedicine, 199, 105874.*
3. *Deng, Y., Lu, L., Aponte, L., Angelidi, A. M., Novak, V., Karniadakis, G. E., & Mantzoros, C. S. (2021). Deep transfer learning and data augmentation improve glucose levels prediction in type 2 diabetes patients. NPJ Digital Medicine, 4(1), 109.*
4. *Guha, D., Avtaran, D. K., Sharma, V., Mishra, S., Lenka, R., & Alkhayyat, A. (2024, December). Chronic Disease Diagnosis Using Multi-modal Transfer Learning Model. In International Conference on Innovations in Data Analytics (pp. 57-67). Singapore: Springer Nature Singapore.*
5. *Gundapaneni, S., Zhi, Z., & Rodrigues, M. (2024). Deep Learning-Based Noninvasive Screening of Type 2 Diabetes with Chest X-ray Images and Electronic Health Records. arXiv preprint arXiv:2412.10955.*
6. *Kaur, C., Al-Ansari, A. R. M., Gongada, T. N., Saravanan, K. A., Rao, D. S., Borda, R. F. C., & Manikandan, R. (2023). Integrating transfer learning and deep neural networks for accurate medical disease diagnosis from multi-modal data. International Journal of Advanced Computer Science and Applications, 14(8).*
7. *Kumar, G. S., & Kumaresan, P. (2024). Deep learning and transfer learning in*

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cardiology: A review of cardiovascular disease prediction models. IEEE Access.

8. *Li, Y., Han, Y., Li, Z., Zhong, Y., & Guo, Z. (2023). A transfer learning-based multimodal neural network combining metadata and multiple medical images for glaucoma type diagnosis. Scientific reports, 13(1), 12076.*

9. *Mohamed Yousuff, A. R., Zainulabedin Hasan, M., Anand, R., & Rajasekhara Babu, M. (2024). Leveraging deep learning models for continuous glucose monitoring and prediction in diabetes management: towards enhanced blood sugar control. International Journal of System Assurance Engineering and Management, 15(6), 2077-2084.*

10. *Rustam, F., Al-Shamayleh, A. S., Shafique, R., Obregon, S. A., Iglesias, R. C., Gonzalez, J. P. M., & Ashraf, I. (2024). Enhanced detection of diabetes mellitus using novel ensemble feature engineering approach and machine learning model. Scientific Reports, 14(1), 23274.*

11. *Selvaraj, A., Satheesh kumar, V., Bhudhwant, D., Tamane, S., & Khandelwal, C. S. (2024, February). Deep Learning Ensemble for Diabetes Prediction: Integrating LSTM, DCNN, and SMOTE for Enhanced Risk Assessment. In International Conference on Computational Intelligence in Data Science (pp. 365-373). Cham: Springer Nature Switzerland.*

12. *Sharma, H., Pundir, S., Deepak, A., Mayuri, K., Dwivedi, S. P., & Kumar, N. (2023, December). Multi-modal data fusion using transfer learning in big data analytics for healthcare. In 2023 International Conference on Artificial Intelligence for Innovations in Healthcare Industries (ICAIIHI) (Vol. 1, pp. 1-7). IEEE.*

13. *Singh, S. B., & Singh, A. (2024). Leveraging Deep Learning and Multi-Modal Data for Early Prediction and Personalized Management of Type 2 Diabetes. International Journal For Multidisciplinary Research, 6(4), 1-9.*

14. *Yoo, T. K., Kim, S. H., Kim, M., Lee, C. S., Byeon, S. H., Kim, S. S., ... & Choi, E. Y. (2022). DeepPDT-Net: predicting the outcome of photodynamic therapy for chronic central serous chorioretinopathy using two-stage multimodal transfer learning. Scientific reports, 12(1), 18689.*

15. *You, F., Zhao, G., Zhang, X., Zhang, Z., Cao, J., & Li, H. (2024). A new multivariate blood glucose prediction method with hybrid feature clustering and online transfer learning. Health Information Science and Systems, 12(1), 57.*