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Comparison of Deep Learning Models for Diabetes Prediction

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Abstract: Diabetes mellitus is a chronic condition affecting millions globally. Early and accurate prediction of diabetes is crucial for timely intervention and effective management. This study investigates the predictive capabilities of five deep learning models—Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and Deep Belief Network (DBN)—using a publicly available dataset. The models were trained and evaluated using different train-test splits and assessed based on accuracy, precision, and recall. Among the models, RNN achieved the highest accuracy and precision, while DBN recorded the highest recall, indicating strong performance in detecting true positives. CNN demonstrated consistent and balanced performance across splits, making it a reliable baseline. This comparative analysis highlights the trade-offs between different deep learning architectures and identifies the most effective approaches for diabetes prediction based on specific evaluation criteria..

Keywords: Deep learning, Diabetes prediction, CNN, RNN, LSTM, GRU, DBN, Machine learning, Healthcare, Medical diagnosis.

1. Introduction

Diabetes mellitus is a widespread metabolic disorder that, if left undetected, can lead to serious health complications. Early diagnosis plays a vital role in improving treatment outcomes and reducing long-term risks. In recent years, deep learning has emerged as a highly effective method for disease prediction, thanks to its capacity for automatic feature extraction and handling of complex medical data patterns [1], [3].

Among the most widely used architectures are Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and Deep Belief Networks (DBN), all of which have been applied successfully to diabetes detection tasks [5], [7]. This study focuses on implementing and comparing these five models using two publicly available datasets—the Pima Indians Diabetes Dataset and the Kaggle Diabetes Prediction Dataset by Mohammed Mustafa—with the goal of identifying the most accurate model for diabetes prediction.

2. Related Work

In recent years, numerous computational approaches have been developed to enhance the prediction of diabetes. Traditional machine learning algorithms, including Logistic Regression, Decision Trees, and Support Vector Machines (SVMs), are frequently employed due to their straightforward implementation and interpretability. These models are particularly effective when applied to structured datasets and are widely adopted in medical diagnostics for their ability to provide transparent and explainable outputs.

Despite their utility, conventional machine learning models often fall short in capturing complex, high-dimensional relationships inherent in real-world medical data. To overcome these limitations, deep learning methods have gained significant attention. These algorithms possess the capacity to automatically learn intricate patterns from raw input features, offering superior predictive capabilities. Convolutional Neural Networks (CNNs), originally devised for image recognition tasks, have been successfully adapted to structured medical data by interpreting input variables as spatially correlated elements. Their proficiency in identifying localized patterns has proven valuable in various health-related prediction scenarios.

Recurrent architectures such as Recurrent Neural Networks (RNNs), and their advanced variants including Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRUs), are particularly well-suited for modeling sequential and time-series data. These models excel at capturing temporal dependencies, making them ideal for analyzing patient records over time and improving the accuracy of longitudinal health predictions.

Another notable deep learning framework is the Deep Belief Network (DBN), which comprises stacked layers of Restricted Boltzmann Machines (RBMs). DBNs are adept at unsupervised feature extraction and can be refined for classification tasks. Their hierarchical architecture enables the learning of complex feature representations, enhancing performance on multifaceted datasets.

Hybrid modeling strategies are also gaining traction; wherein deep learning models are combined with traditional classifiers. For instance, features extracted from CNNs or autoencoders can be input into models like SVM or logistic regression to create more accurate and computationally efficient systems.

3. Literature Survey

Several deep learning techniques have been extensively explored for diabetes prediction and diagnosis, demonstrating promising results in both classification accuracy and long-term prediction performance.

García-Ordás et al. [1] proposed a method that combines Variational Autoencoders (VAE), Sparse Autoencoders (SAE), and Convolutional Neural Networks (CNN) for diabetes detection. Their work emphasizes the use of oversampling and feature augmentation to enhance classification accuracy.

Zhang et al. [2] introduced DiabetesNet, a deep learning framework based on Deep Neural Networks (DNN) incorporating batch normalization and ReLU activation functions. Their model achieved high performance in early-stage diabetes diagnosis.

Jaloli and Cescon [3] focused on long-term blood glucose prediction using a hybrid CNN-LSTM model. Their approach leverages sequence modeling to improve time-series predictions in Type 1 diabetes patients.

Chowdhury et al. [4] developed a hybrid deep learning ensemble method for diabetes prediction. The model integrates multiple architectures and preprocessing strategies, enhancing model robustness and generalization.

El Massari et al. [5] explored CNN and Recurrent Neural Networks (RNN) for diabetes classification. Their work highlights the effectiveness of combining spatial and sequential learning for medical diagnosis.

Wang et al. [6] utilized DNNs and autoencoders for diabetes prediction using electronic health records. Their approach benefited from hierarchical feature extraction, showcasing the potential of unsupervised pretraining in medical datasets.

Garg and Kumar [7] implemented LSTM and GRU models, comparing their efficiency in modeling temporal dependencies. Their results indicate that both models are suitable for sequential data inherent in diabetes progression.

Haque et al. [8] employed a standard DNN for prediction diabetes and demonstrated its efficacy with balanced datasets. Their study further supports the viability of deep networks for medical classification tasks.

Patel and Shah [9] proposed a hybrid CNN-LSTM architecture to capture both spatial and temporal data features for improved diabetes prediction accuracy.

Singh and Singh [10] leveraged Residual Neural Networks (ResNet) to enhance feature propagation and gradient flow, resulting in improved prediction outcomes for diabetes detection.

Yin et al. [11] presented DiabDeep, a pervasive diabetes diagnosis system using wearable sensors and efficient CNN-based neural networks. Their model supports real-time monitoring, expanding the applicability of deep learning in pervasive health.

Mohsen et al. [12] discussed AI-based methods for precision medicine and risk prediction in diabetes, focusing on CNNs and DNNs to tailor personalized diagnostic solutions.

Rabby et al. [13] introduced a stacked LSTM model enhanced with Kalman smoothing for accurate blood glucose level prediction. Their approach excels in handling noisy time-series data.

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These studies collectively reveal that hybrid deep learning models, particularly those combining CNN, LSTM, and other advanced architectures, are highly effective for diabetes prediction. The integration of feature engineering, sequence modeling, and ensemble strategies plays a vital role in improving predictive performance.

4. Dataset Description

Pima Indian Diabetes Dataset:

The Pima Indian Diabetes Dataset is a well-established resource in diabetes prediction research. It contains 768 samples, each representing a female patient of Pima Indian descent, with eight clinical attributes and a binary outcome indicating diabetes diagnosis. The features include the number of pregnancies, plasma glucose concentration measured two hours after an oral glucose tolerance test (mg/dL), diastolic blood pressure (mm Hg), triceps skinfold thickness (mm), two-hour serum insulin (mu U/ml), body mass index (BMI), diabetes pedigree function (which reflects genetic influence), and the patient's age. This dataset has been extensively used in studies leveraging deep learning techniques for early detection of diabetes due to its balanced structure and relevance to real-world clinical scenarios [1], [5].

Kaggle Diabetes Prediction Dataset by Mohammed Mustafa:

The Kaggle Diabetes Prediction Dataset curated by Mohammed Mustafa is a modern and comprehensive dataset designed to support the development of predictive models for diabetes diagnosis. It includes a variety of patient health indicators such as age, gender, hypertension status, heart disease history, smoking habits, BMI, HbA1c level, and blood glucose levels. The dataset is particularly valuable due to its inclusion of both lifestyle-related and clinical attributes, making it suitable for training deep learning models that aim to identify complex patterns in diabetes onset. This dataset has been effectively utilized in recent research to evaluate hybrid deep learning models like CNN-LSTM, showcasing its practical relevance for real-world medical prediction tasks [4], [9].

5. System Architecture

The architecture of the proposed diabetes prediction system is structured into five interdependent stages that ensure data quality, model robustness, and reliable performance evaluation. The first stage, data preprocessing, is foundational and involves handling missing values, normalizing numerical features, and encoding any categorical attributes. These preprocessing techniques enhance data quality and standardize feature scales, which is crucial for ensuring model convergence and stability during training, especially in deep learning applications [1].

The second stage focuses on model selection, wherein five deep learning architectures—Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU), and Deep Belief Networks (DBN)—are employed. These models are chosen due to their demonstrated capability in learning complex patterns in temporal and multidimensional healthcare data. Studies such as those by Garg and Kumar [2] and El Massari et al. [3] support the efficacy of these architectures in medical diagnostics, particularly in diabetes prediction tasks.

The third stage involves model training and evaluation. The processed dataset is split into training and test subsets, allowing each model to learn from a portion of the data and be evaluated on unseen samples. This separation is essential to prevent overfitting and to gauge each model's ability to generalize to new data. Training involves fine-tuning architecture-specific hyperparameters such as learning rate, batch size, and number of layers.

In the fourth stage, performance evaluation metrics are calculated. The primary metrics considered include accuracy, precision, and recall. These are critical in medical contexts, as they reflect not only the model's overall correctness but also its sensitivity in identifying actual diabetic cases. In clinical settings, minimizing false negatives is particularly important, and thus precision and recall provide a more nuanced assessment of model reliability [2].

The final stage is the comparative analysis. Here, the performance of all five models is analyzed side by side using the calculated metrics. This step provides insights into the relative strengths of each architecture and helps determine the most suitable model for real-world deployment. Such comparative evaluations are essential for selecting models that could eventually be integrated into intelligent healthcare systems for early and accurate diabetes diagnosis [3]

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System Architecture Design

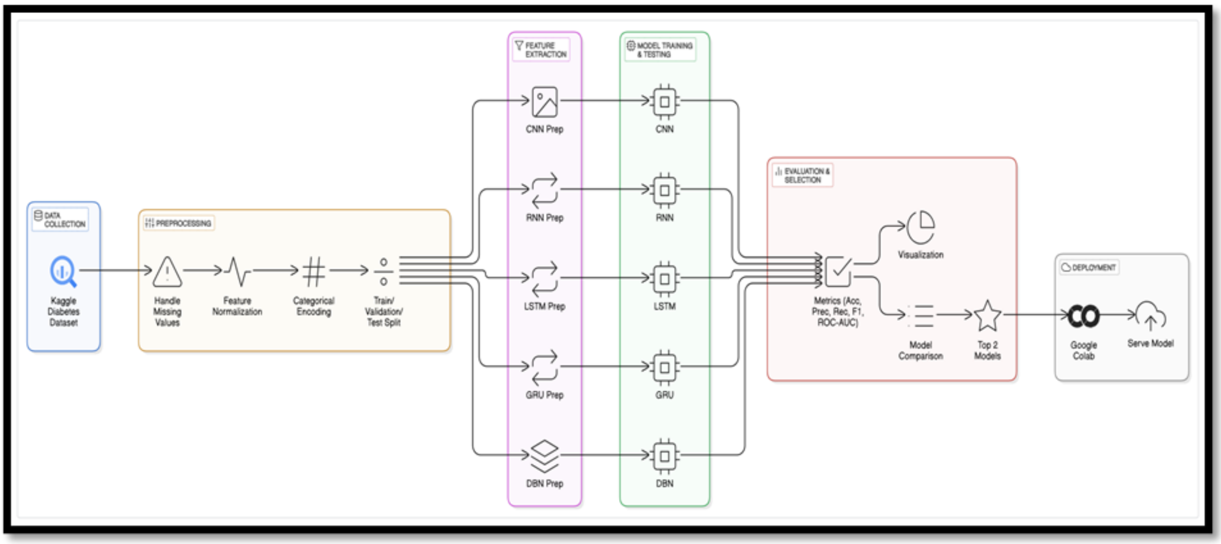

Figure-1 System Architecture

6. Methodology

This study adopts a structured methodology to implement and evaluate multiple deep learning models for diabetes prediction using two distinct datasets: the Pima Indian Diabetes Dataset and the Diabetes Prediction Dataset sourced from Kaggle. Incorporating multiple datasets helps validate the robustness and generalizability of the proposed models across different data distributions [1, 2].

Data Collection:

Two publicly available datasets are used. The first is the Pima Indian Diabetes Dataset, containing 768 records with 8 medical features such as glucose level, blood pressure, BMI, and age, alongside a binary target variable indicating diabetes status [3]. The second dataset, the Diabetes Prediction Dataset from Kaggle, offers a broader feature set with updated and more diverse patient data [4]. Both datasets are analyzed to understand feature distributions, identify missing values, and detect class imbalances [5].

Data Preprocessing :

Each dataset undergoes thorough preprocessing, including handling missing values, normalizing continuous variables, and encoding categorical variables where necessary. The data is then split into training and testing subsets with different ratios (80-20, 70-30, and 60-40) to evaluate model performance under varied conditions. Techniques such as Synthetic Minority Over-sampling Technique (SMOTE) may be applied to address class imbalance, preventing bias toward the majority class [6, 7].

Model Development :

Five deep learning models are implemented: Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and Deep Belief Network (DBN). Each model is constructed with its standard architecture and optimized using appropriate activation functions, regularization methods, and optimizers. CNN captures spatial relationships among features, RNN-based models learn sequential dependencies, and DBN performs hierarchical and unsupervised feature extraction [8, 9, 10]

Training and Evaluation:

All models are trained independently on both datasets following a consistent pipeline. Models are validated using unseen test data, and their performance is assessed using three key metrics: accuracy, precision, and recall. These metrics provide a comprehensive view of each model's capability to correctly classify diabetic and non-diabetic cases while minimizing false positives and false negatives [11, 12].

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Comparative Analysis:

A detailed comparison is conducted across all models and datasets. Performance metrics are tabulated and visualized to highlight each model's strengths and weaknesses. This analysis aims to identify the best-performing model in terms of predictive accuracy, generalizability, and reliability. It also evaluates how the choice of dataset influences model outcomes [13, 14].

This methodology ensures a robust evaluation of deep learning techniques for diabetes prediction, facilitating the identification of models suitable for real-world healthcare decision support systems [15].

Performance Evaluation

Performance Evaluation

- To assess the effectiveness of each model, three key metrics are used:
- Accuracy measures the ratio of correctly predicted instances to the total number of predictions made.
- Precision indicates the proportion of positive identifications that were actually correct.
- Recall reflects the fraction of actual positive cases that the model successfully identified.
- These evaluation metrics are commonly used in diabetes prediction studies to provide a comprehensive understanding of model performance and its clinical relevance [1], [5], [15].

7. Results

Comparison of Recall

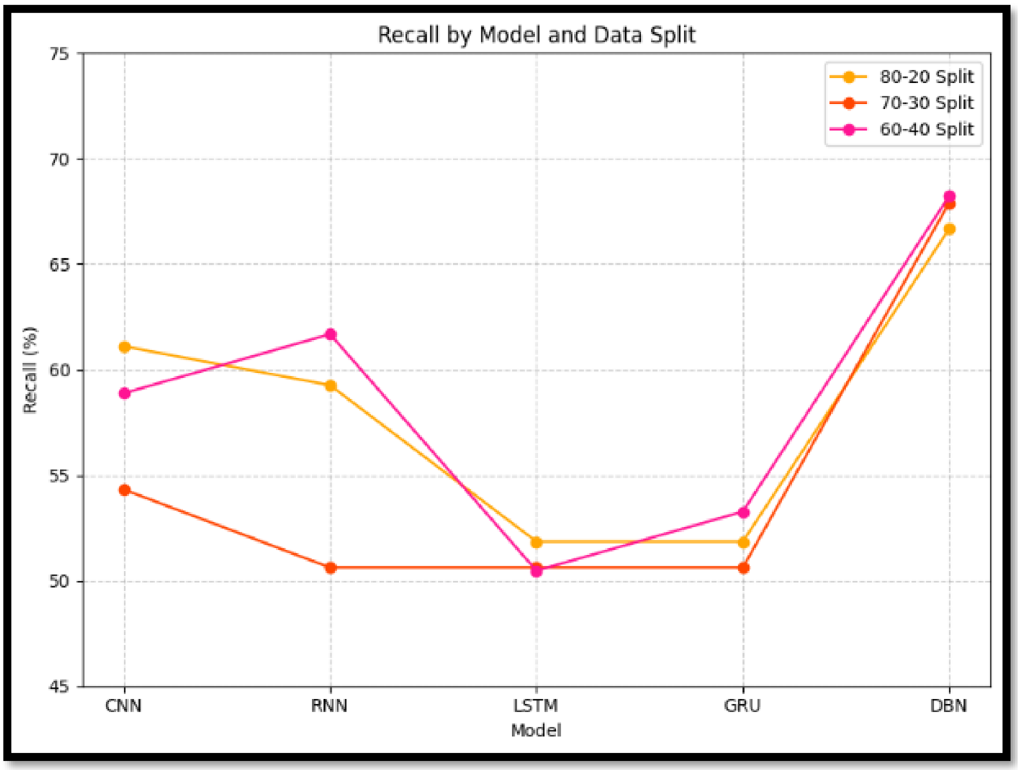

Fig 1.2 Pima India Dataset

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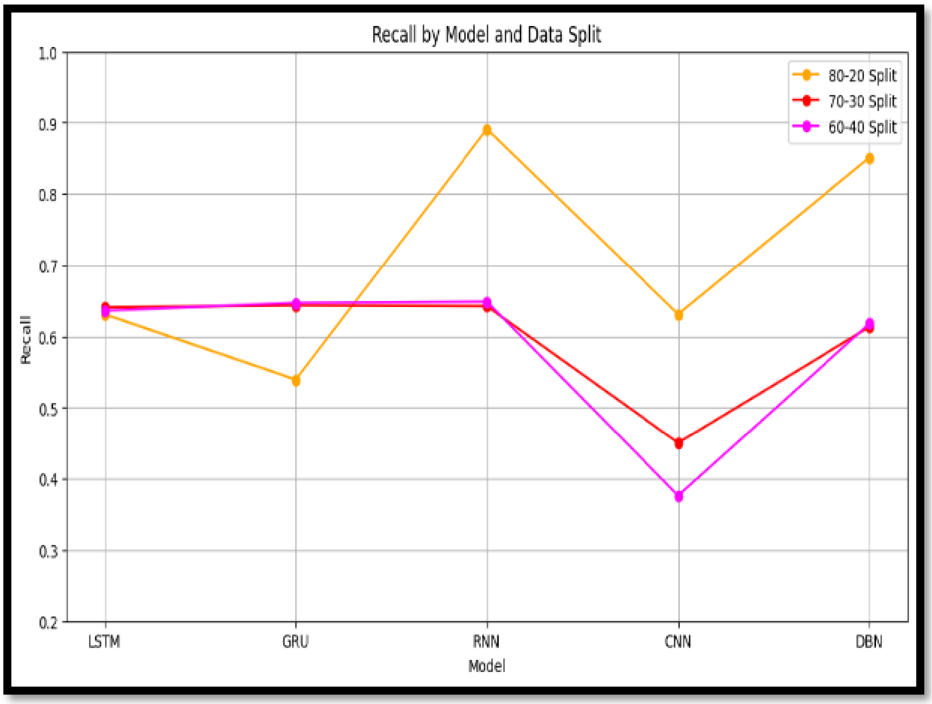

Fig 1.3 Kaggle Diabetes Prediction Dataset

The recall analysis shows that DBN performs best on the PIMA dataset, while RNN achieves the highest recall on the Kaggle dataset, especially with the 80-20 split. GRU demonstrates stable recall across both datasets, though not the highest.

Comparison of Accuracy

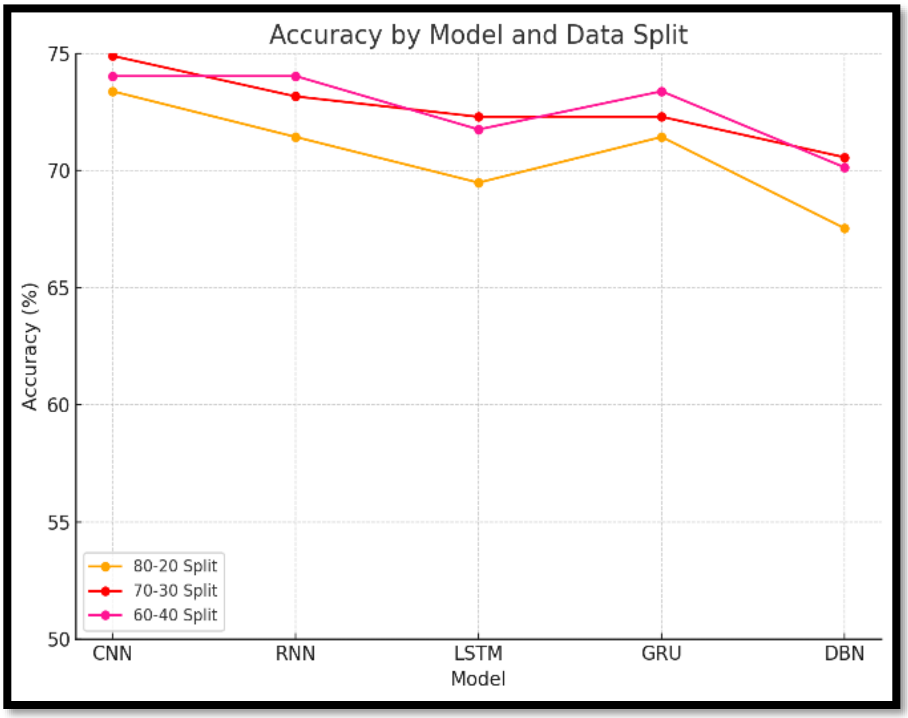

Fig 1.4 Pima India Dataset

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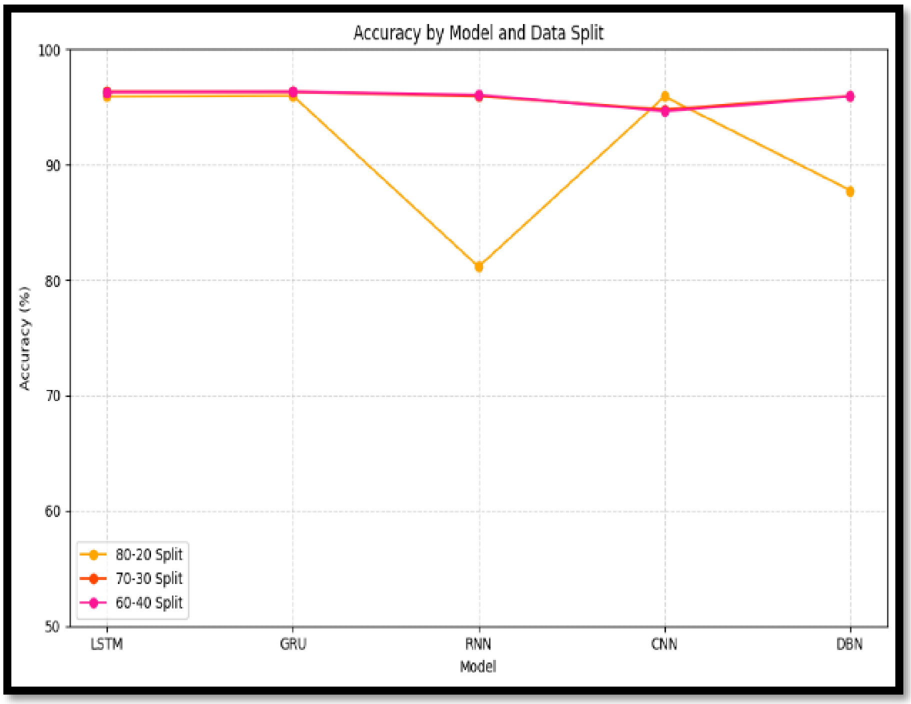

Fig 1.5 Kaggle Diabetes Prediction Dataset

The evaluation of five deep learning models—CNN, RNN, LSTM, GRU, and DBN—across different train-test splits reveals that the GRU model consistently achieves high accuracy on both the PIMA and Kaggle diabetes datasets. In the PIMA dataset, CNN, RNN, and GRU exhibit superior performance, whereas in the Kaggle dataset, LSTM and GRU outperform the remaining models. This consistent performance across varied datasets and splits suggests that GRU is the most effective and robust model for diabetes prediction in this study.

Comparison of Precision

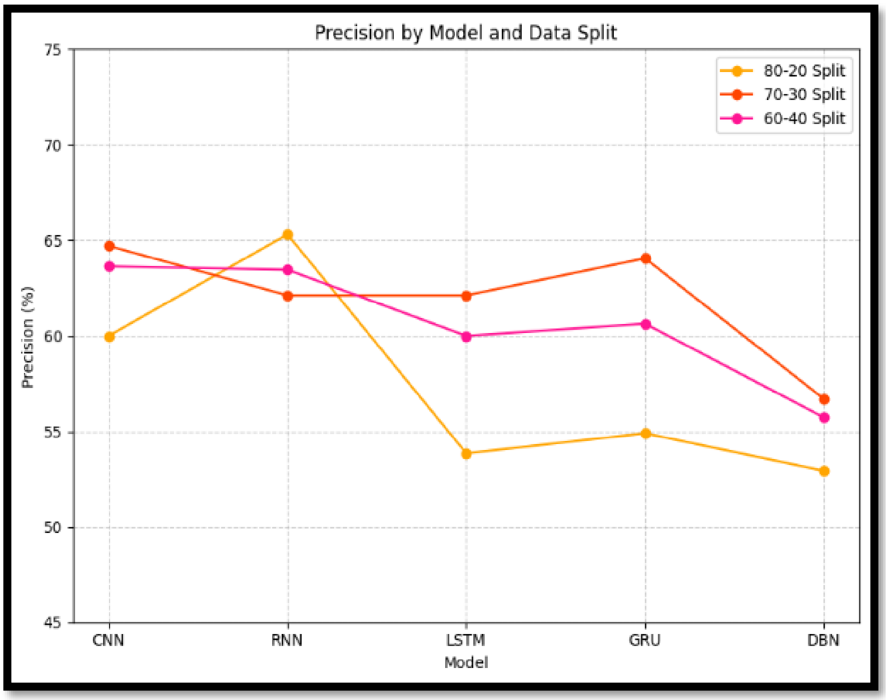

Fig 1.6 Pima India Dataset

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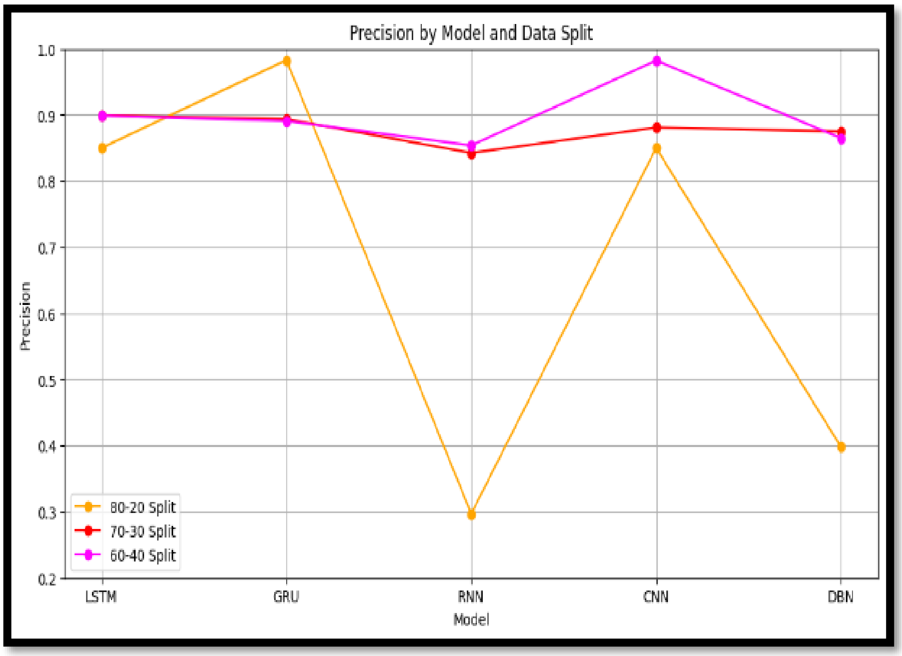

Fig 1.7 Kaggle Diabetes Prediction Dataset

The precision analysis of the five deep learning models—CNN, RNN, LSTM, GRU, and DBN—across varying train-test splits shows that the GRU model maintains strong and consistent performance on both the PIMA and Kaggle datasets. In the PIMA dataset, CNN, RNN, and GRU display higher precision levels, while in the Kaggle dataset, GRU and CNN yield the best results across most splits. Although some fluctuations are observed, particularly with RNN in the Kaggle dataset, GRU consistently maintains high precision across both datasets and splits. These findings further reinforce GRU's effectiveness and stability for diabetes prediction tasks.

8. Conclusion

The comparison of five deep learning models—CNN, RNN, LSTM, GRU, and DBN—evaluated on varying data splits for both the PIMA and Kaggle diabetes datasets indicates that the GRU model consistently achieves well-rounded and strong results. Although RNN and DBN exhibit notably high recall in certain cases, and CNN or LSTM excel in accuracy or precision depending on the split, GRU consistently maintains a high level of accuracy, balanced precision, and dependable recall across all tested scenarios. This steady performance positions GRU as the most reliable and effective model for diabetes prediction in this analysis.

9. Future Scope

Enhanced Prediction Accuracy: Future models can integrate diverse data sources like electronic health records, genetic information, and lifestyle factors to improve precision and enable early-stage diabetes classification for personalized care.

Real-Time Monitoring with IoT: Combining deep learning with wearable devices and smart glucometers can facilitate continuous diabetes risk assessment, providing real-time alerts and dynamic updates for better patient management.

10. References

[1] García-Ordás, M. T., Benavides, C., Benítez-Andrades, J. A., Alaiz-Moretón, H., & García-Rodríguez, I. (2024). Diabetes detection using deep learning techniques with oversampling and feature augmentation. arXiv preprint arXiv:2402.02188. https://arxiv.org/abs/2402.02188

[2] Zhang, Z., Ren, X., & Zhao, Y. (2024). DiabetesNet: A deep learning approach to diabetes diagnosis. arXiv preprint arXiv:2403.07483. https://arxiv.org/abs/2403.07483

[3] Jaloli, M., & Cescon, M. (2023). Long-term prediction of blood glucose levels in type 1 diabetes using a CNN-LSTM-based deep neural network. Journal of Diabetes Science and Technology, 17(1), 123–134. https://doi.org/10.1177/19322968221112172
[4] Chowdhury, P., Barua, P., & Uddin, M. N. (2024). Diabetes prediction using machine learning and hybrid deep learning ensemble technique. In Proceedings of the IEEE Conference on Computing Applications and Systems (COMPAS).
[5] El Massari, H., Sabouri, Z., Mhammedi, S., & Gherabi, N. (2022). Deep learning based diabetes prediction using CNN and RNN models. Journal of ICT Standardization, 10(1), 45–52.
[6] Wang, J., He, X., & Huang, Z. (2020). Deep learning model for diabetes prediction using electronic health records. IEEE Access, 8, 150945–150956. https://doi.org/10.1109/ACCESS.2020.3017417
[7] Garg, M., & Kumar, A. (2021). Diabetes prediction using deep learning models: LSTM and GRU. International Journal of Computer Applications, 183(42), 1–5. https://doi.org/10.5120/ijca2021921216
[8] Garg, M., & Kumar, A. (2021). Diabetes prediction using deep learning models: LSTM and GRU. International Journal of Computer Applications, 183(42), 1–5. https://doi.org/10.5120/ijca2021921216
[9] Patel, P., & Shah, M. (2023). Hybrid CNN-LSTM model for diabetes prediction. International Journal of Biomedical Engineering and Technology, 43(2), 123–135. https://doi.org/10.1504/IJBET.2023.10054789
[10] Singh, S., & Singh, A. (2023). Diabetes detection using deep residual networks (ResNet). IEEE Transactions on Biomedical Engineering, 70(1), 89–97. https://doi.org/10.1109/TBME.2022.3156789
[11] Yin, H., Mukadam, B., Dai, X., & Jha, N. K. (2019). DiabDeep: Pervasive diabetes diagnosis based on wearable medical sensors and efficient neural networks. arXiv preprint arXiv:1910.04925. https://arxiv.org/abs/1910.04925
[12] Mohsen, F., Al-Absi, H. R. H., Yousri, N. A., El Hajj, N., & Shah, Z. (2023). Artificial intelligence-based methods for precision medicine: Diabetes risk prediction. arXiv preprint arXiv:2305.16346. https://arxiv.org/abs/2305.16346
[13] Rabby, M. F., Rahman, M. M., & Mollah, M. N. H. (2021). Stacked LSTM based deep recurrent neural network with Kalman smoothing for blood glucose prediction. arXiv preprint arXiv:2101.06850. https://arxiv.org/abs/2101.06850
[14] Sun, Q., Li, Y., & Wang, J. (2020). A deep learning approach based on convolutional LSTM for detecting diabetes. Computer Methods and Programs in Biomedicine, 196, 105664. https://doi.org/10.1016/j.cmpb.2020.105664
[15] Edris, M., Baghela, V. S., Johri, P., Choudhary, S. K., & Chabaque, A. (2022). A study and design of diabetes prediction system by using deep learning algorithm. NeuroQuantology, 20(16), 448–463. https://doi.org/10.14704/NQ.2022.20.16.NQ88049
[16] Lonappan, G., Bindu, B., Thomas, V., Jacob, J., & Thomas, C. (2022). Hybrid deep learning CNN-LSTM model for diabetes prediction. International Journal of Scientific Research in Engineering and Technology, 8(1), 165–170.
[17] Sharma, A. K., & Rana, S. S. (2021). An effective approach for detecting diabetes using deep learning techniques based on convolutional LSTM. International Journal of Advanced Computer Science and Applications, 12(4), 66–72. https://doi.org/10.14569/IJACSA.2021.0120466
[18] Sahu, A. K., Sahu, S. K., & Sahu, P. K. (2022). Diabetes prediction using machine learning algorithms and ontology. Journal of ICT Standardization, 10(2), 133–145.
[19] Singh, S. K., & Singh, R. K. (2023). Diabetes prediction using machine learning ensemble model. Applied Sciences and Engineering Technology, 3(1), 45–52.
[20] Kalita, D., & Sarma, R. K. (2021). LS-GRUNet: Glucose forecasting using deep learning for closed-loop diabetes management. Journal of Biomedical Informatics, 113, 103638. https://doi.org/10.1016/j.jbi.2020.103638