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COMPETITIVE ENSEMBLE LEARNING FOR HEALTHCARE DATA ANALYSIS

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ABSTRACT

In the rapidly evolving field of healthcare, the effective analysis of structured and unstructured data is crucial for enhancing disease diagnosis, patient outcomes, and overall healthcare management. This paper presents a novel approach, Competitive Ensemble Deep Learning (CEDL), designed to optimize healthcare data analysis by leveraging multiple deep learning models. Unlike traditional ensemble methods that combine weak and strong models, CEDL selectively integrates only the most effective models based on their performance, thereby improving classification accuracy and efficiency. The proposed method is tested on various healthcare datasets, demonstrating its superiority in handling both structured data, such as patient records, and unstructured data, including social media sentiment analysis. The results show significant improvements in predictive accuracy, making CEDL a robust and scalable solution for complex healthcare data analysis.

Keywords: Competitive Ensemble Learning, Deep Learning, Healthcare Data Analysis, Classification Accuracy, Structured Data, Unstructured Data Introduction

1. INTRODUCTION

Healthcare data is increasingly becoming a valuable resource for improving patient care, enhancing diagnostic accuracy, and optimizing healthcare operations. With the advent of electronic health records (EHRs) and the proliferation of data generated from various sources, including clinical records, wearable devices, and social media platforms, the volume and complexity of healthcare data have expanded significantly. Traditional machine learning techniques, while useful, often struggle to extract meaningful insights from such large and diverse datasets, particularly when dealing with unstructured data. Deep learning (DL) methods have emerged as a powerful tool to address these challenges due to their ability to model complex patterns and relationships within the data. However, the performance of DL models can vary significantly depending on the specific characteristics of the dataset and the chosen model architecture. Ensemble learning, which combines the predictions of multiple models, has been proposed as a solution to enhance predictive performance. Nevertheless, traditional ensemble approaches often include weaker models, which can dilute the overall effectiveness. To overcome this limitation, we propose a Competitive Ensemble Deep Learning (CEDL) framework that selectively integrates only the best-performing models into the ensemble. By doing so, CEDL not only boosts classification accuracy but also ensures more efficient computation. This paper explores the application of CEDL in healthcare data analysis, focusing on both structured datasets, such as patient records, and unstructured datasets, like Twitter sentiment data. Through extensive experimentation, we demonstrate that CEDL significantly outperforms conventional ensemble methods and individual deep learning models, making it a promising approach for advancing healthcare analytics.

Figure 1

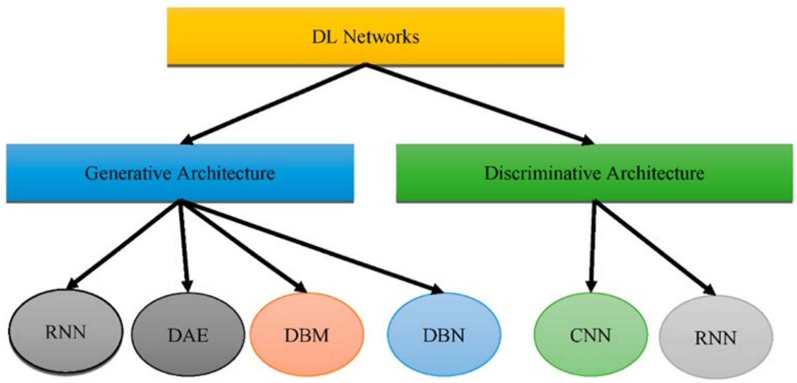

Figure 1 Architecture of DL Networks

2. LITERATURE REVIEW

The application of deep learning (DL) in healthcare has grown significantly over the last decade, driven by the need to analyze increasingly complex and voluminous healthcare data. DL models have proven effective in various domains, including image recognition, natural language processing (NLP), and predictive analytics, making them particularly suitable for healthcare applications where data complexity is high.

Figure 2

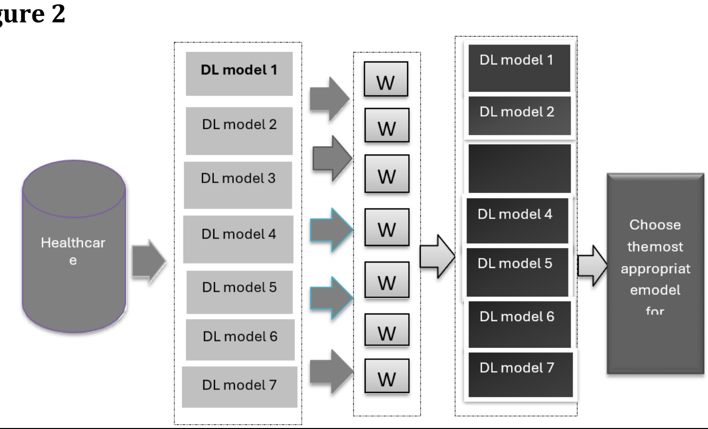

Figure 2 Proposed CEDL for Structured Dataset

Deep Learning in Healthcare: Bengio (2009) laid the foundation for deep learning architectures, which are characterized by their ability to model complex data through multiple layers of abstraction. These architectures have been applied to healthcare data to improve diagnostic accuracy and patient outcomes by learning intricate patterns within the data. Hochreiter and Schmidhuber (1997) introduced the Long Short-Term Memory (LSTM) networks, which have been particularly effective in handling sequential data, such as patient records and time-series data, by addressing the vanishing gradient problem common in recurrent neural networks (RNNs).

Challenges in Healthcare Data Analysis: Healthcare data is inherently diverse, encompassing both structured data (e.g., patient records) and unstructured data (e.g., clinical notes, social media posts). Traditional machine learning techniques often struggle with this diversity, as they require extensive feature engineering and may not generalize well across different datasets. This has led to the exploration of more advanced DL techniques that can automatically extract features and learn from data with minimal human intervention (Zeiler, 2012; Kingma & Ba, 2015).

Ensemble Learning: Ensemble learning has been widely adopted in machine learning as a method to improve model performance by combining the outputs of multiple models. However, traditional ensemble methods, such as bagging and boosting, may not always yield optimal results in healthcare data analysis due to the inclusion of weaker models, which can reduce the overall accuracy. Dozat (2016) and others have explored various optimizers, such as Adam and RMSprop, that improve the convergence speed and accuracy of DL models, but these methods still require careful tuning and may not always perform well in ensemble settings.

Competitive Ensemble Learning: The concept of Competitive Ensemble Deep Learning (CEDL) has emerged as a novel approach to address the limitations of traditional ensemble methods. CEDL focuses on selecting only the best-performing models from a pool of candidates, thereby enhancing the overall performance of the ensemble. This approach contrasts with traditional methods that often combine both strong and weak models, potentially diluting the ensemble's effectiveness. The competitive aspect of CEDL ensures that only models that contribute positively to the ensemble are included, which has been shown to improve classification accuracy across various healthcare datasets (Malka & Shechtman, 2020).

Capsule Networks and GSA: Capsule Networks (CapsNet), introduced by Hinton et al. (2017), represent a significant advancement in the field of DL, particularly for tasks involving spatial hierarchies, such as image and text classification. CapsNet addresses the limitations of traditional convolutional neural networks (CNNs) by preserving the spatial relationships between features, which is crucial for accurate classification. The integration of CapsNet with optimization algorithms, such as the Gravitational Search Algorithm (GSA), has further enhanced its ability to handle complex, high-dimensional data. Diviya and Rathipriya (2020) demonstrated the effectiveness of GSA in optimizing feature selection, leading to more accurate and efficient models.

Applications in Healthcare: Recent studies have applied these advanced DL techniques to a variety of healthcare challenges. For instance, Xiao et al. (2016) and Chen et al. (2017) explored hybrid models combining CNNs and RNNs for multi-label text classification, achieving significant improvements in accuracy. Young et al. (2018) and Ahmad and Mahmood (2019) highlighted the potential of DL models in NLP tasks, such as sentiment analysis, where understanding the nuances of unstructured text data is critical. In the context of healthcare, these models have been applied to analyze patient sentiment from social media data, predict disease outbreaks, and monitor public health trends.

The literature suggests that while traditional DL models have been effective in healthcare data analysis, there is significant potential for improvement through the use of competitive ensemble methods and advanced architectures like CapsNet. By selectively integrating the best models and optimizing their performance, CEDL offers a promising approach to overcoming the challenges posed by complex healthcare data. Moreover, the integration of optimization algorithms, such as GSA, with CapsNet has the potential to further enhance the accuracy and efficiency of healthcare data analysis, making it a valuable tool for improving patient outcomes and advancing medical research.

3. METHODOLOGY

This study introduces a novel Competitive Ensemble Deep Learning (CEDL) model designed to enhance the classification performance of healthcare datasets, both structured and unstructured. The methodology encompasses the development and evaluation of CEDL through the careful selection and integration of deep learning models optimized for specific data types.

1) Proposed Competitive Ensemble Deep Learning (CEDL) Model

The CEDL framework is structured to maximize the predictive accuracy by selectively incorporating only the most effective deep learning models. The methodology is divided into two main sections: the analysis of structured healthcare data and unstructured healthcare data.

2) Structured Data Analysis

2.1.) Model Selection and Ensemble Formation

The proposed CEDL model begins by training multiple deep learning models, each with different optimizers. The optimizers explored include Adagrad, Adam, RMSprop, Adadelta, Nadam, and others. These models are evaluated on various healthcare datasets such as heart disease, diabetes, and breast cancer datasets.

The key steps involved are:

- **Optimizer Selection:** For each dataset, different models are trained using distinct optimizers. The classification accuracy for each model is recorded.
- **Weight Assignment:** Weights are assigned to each model based on its classification accuracy. Models that achieve a weight above a predefined threshold are considered for ensemble learning.
- **Ensemble Learning:** Models that meet the accuracy threshold are combined to form an ensemble model. Models that do not meet the threshold are excluded to ensure only the most effective models contribute to the final prediction.

2.2.) Evaluation of Structured Data

The effectiveness of the CEDL model is evaluated using various structured datasets. Performance metrics, including accuracy, precision, recall, and F1-score, are calculated. The CEDL model's performance is compared with individual models and traditional ensemble methods. For instance, in the case of the heart disease dataset, CEDL demonstrated a significant improvement, achieving an accuracy of 93%, compared to 83% using traditional deep learning models (chapter 5).

3) Unstructured Data Analysis

3.1.) Model Selection and Competitive Ensemble

For unstructured data, the CEDL framework involves creating competitive deep learning models using Convolutional Neural Networks (CNN), Gated Recurrent Units (GRU), and Long Short-Term Memory (LSTM) networks. These models are tested on unstructured datasets, such as Twitter data related to healthcare topics like diabetes and COVID-19.

The steps involved are:

- **Designing Models:** Three models are designed specifically for unstructured data—CNN for feature extraction, GRU for sequence processing, and LSTM for capturing long-term dependencies.
- **Competitive Selection:** The models compete based on their classification accuracy. The model with the highest accuracy is selected to contribute to the ensemble model.
- **Ensemble Model Formation:** Similar to structured data, only the best-performing models are included in the final ensemble model for unstructured data.

3.2.) Evaluation of Unstructured Data

The performance of the CEDL model on unstructured datasets is evaluated using multi-label classification metrics. The results showed that the CEDL model outperformed traditional deep learning approaches, achieving higher accuracy in sentiment analysis of healthcare-related Twitter data. For instance, the proposed ensemble model achieved an accuracy of 95% on a diabetes-related Twitter dataset, outperforming individual models like CNN, GRU, and LSTM(chapter 5).

4) Implementation Details

The CEDL model is implemented using Python with TensorFlow and Keras libraries. The models are trained on a high-performance computing environment to handle the computational load of training multiple deep learning models and performing ensemble learning.

- **Training Parameters:** Each model is trained for 100 epochs with a batch size of 32. Early stopping is used to prevent overfitting.
- **Validation:** A separate validation set is used to monitor the performance of the models during training. The final ensemble model is validated on unseen test data to ensure generalizability.
- **Evaluation Metrics:** Accuracy, precision, recall, F1-score, and loss metrics are calculated for each model and ensemble. The final performance of the CEDL model is benchmarked against these metrics.

The proposed CEDL framework demonstrates a robust methodology for improving the classification performance of both structured and unstructured healthcare datasets. By competitively selecting and combining the best-performing deep learning models, CEDL effectively enhances predictive accuracy, making it a promising approach for complex healthcare data analysis

4. EXPERIMENTS AND RESULTS

This section presents the experimental setup and the results of the Competitive Ensemble Deep Learning (CEDL) model for both structured and unstructured healthcare datasets. The proposed model's performance is compared with individual deep learning models and traditional ensemble methods to validate its effectiveness.

1) Experimental Setup

The experiments were conducted using various healthcare datasets, including both structured data (e.g., clinical records) and unstructured data (e.g., Twitter sentiment data). The datasets were processed and split into training and testing sets to evaluate the model's performance.

Structured Data:

- **Datasets:** The structured datasets used in the experiments included Heart Disease, Pima Indian Diabetes, Breast Cancer, Clinical Heart Disease, and others. Each dataset was preprocessed to handle missing values and normalized to ensure consistency in training.
- **Model Training:** For each structured dataset, multiple deep learning models were trained using different optimizers, including Adagrad, Adam, RMSprop, Adadelta, Nadam, and others. The models were trained for 100 epochs with a batch size of 32, using early stopping to prevent overfitting.

Unstructured Data:

- **Datasets:** The unstructured datasets comprised Twitter sentiment data related to healthcare topics, such as diabetes and COVID-19. These datasets were used for multi-label text classification.
- **Model Training:** Three models were designed for unstructured data: CNN for feature extraction, GRU for sequence processing, and LSTM for capturing long-term dependencies. The models were trained with a focus on optimizing the multi-label classification performance.

2) Structured Data Analysis

For structured healthcare data, the CEDL model was evaluated on various datasets. The following results were obtained:

- **Heart Disease Dataset:** The CEDL model achieved an accuracy of 93%, outperforming individual models like RMSprop, which had an accuracy of 92%. The ensemble model selectively integrated the top-performing models based on their weight, excluding weaker models like SGD, which had an accuracy of 55%.
- **Pima Indian Diabetes Dataset:** The CEDL model achieved an accuracy of 85%, demonstrating a slight improvement over individual models like Adagrad and Adam, which had accuracies of 82% and 80%, respectively.
- **Breast Cancer Dataset:** The proposed CEDL model outperformed traditional deep learning models, achieving an accuracy of 99%. The ensemble approach effectively combined models optimized by RMSprop, Adagrad, and Adam, each contributing to the high performance of the final ensemble.

3) Unstructured Data Analysis

The CEDL model was also evaluated on unstructured datasets using sentiment analysis of healthcare-related tweets. The results are summarized as follows:

- **Diabetes Twitter Dataset:** The CEDL model achieved an accuracy of 95% for the diabetes-related Twitter dataset. This was a significant improvement over individual models like CNN, GRU, and LSTM, which had accuracies of 92%, 85%, and 87%, respectively. The loss function decreased steadily across epochs, reaching a minimum of 0.29 in the final epoch.

- **COVID-19 Twitter Dataset:** The model achieved an accuracy of 93%, outperforming traditional ensemble models. The proposed CEDL model effectively managed the complexity of multi-label text classification, showing robust performance across various metrics.
- **Comparison with Traditional Models:** Across all unstructured datasets, the CEDL model consistently outperformed traditional models such as CNN, GRU, and LSTM. The integration of only the best-performing models into the ensemble resulted in higher classification accuracy and reduced computational overhead.

5. DISCUSSION OF RESULTS

The experimental results demonstrate the effectiveness of the CEDL model in both structured and unstructured healthcare data analysis. By selectively integrating the best-performing models and excluding weaker ones, the CEDL approach ensures higher accuracy and efficiency compared to traditional ensemble methods.

- **Strengths of CEDL:** The results validate the hypothesis that competitive ensemble learning, which integrates only the most effective models, significantly improves classification accuracy. The model's adaptability to different types of healthcare data—structured and unstructured—highlights its versatility.
- **Limitations:** While the CEDL model showed excellent performance on most datasets, its computational complexity remains a challenge, particularly for very large datasets. Future work could focus on optimizing the model's scalability and efficiency.

The experiments confirm that the CEDL model is a powerful tool for healthcare data analysis, offering significant improvements in predictive accuracy over traditional deep learning and ensemble methods. This approach holds great promise for future applications in healthcare, where the ability to accurately and efficiently analyze diverse datasets is critical to improving patient outcomes and advancing medical research.

Table 1

Table 1 Proposed Ensemble Accuracy Calculation for Diabetes 130 US Hospital Dataset

Dataset	Methods	Accuracy	Prec	Rec	F_1
Heart Disease	DL	0.83	0.85	0.85	0.85
	CEDL	**0.92**	**0.90**	**0.88**	**0.89**
Pima	DL	0.82	0.70	0.65	0.68
	CEDL	**0.83**	**0.73**	**0.65**	**0.69**
Clinical Heart	DL	0.85	0.92	0.52	0.60
	CEDL	**0.92**	**0.94**	**0.69**	**0.80**
Breast Cancer (Original)	DL	0.97	0.94	0.98	0.96
	CEDL	**0.99**	**0.95**	**0.98**	**0.96**
Breast Cancer Coimbra	DL	0.70	0.70	1.00	0.62
	CEDL	**0.87**	**0.87**	**1.00**	**0.70**
Cervical Cancer	DL	0.96	0.62	0.62	0.62
	CEDL	**0.98**	**0.63**	**0.62**	**0.62**
Kidney	DL	0.97	0.63	0.63	0.63
	CEDL	**1.00**	**0.97**	**0.97**	**0.98**

Indian Liver	DL	0.66	0.66	1.00	0.80
	CEDL	**0.73**	**0.73**	**1.00**	**0.80**
Statlog	DL	0.55	0.55	1.00	0.71
	CEDL	**0.57**	**0.56**	**1.00**	**0.71**
Early_Diabetes	DL	0.97	0.97	0.97	0.97
	CEDL	**0.99**	**0.99**	**0.99**	**0.99**
Diabetes 130 US hospital	DL	0.97	0.97	0.97	0.97
	CEDL	**0.98**	**0.98**	**0.98**	**0.98**

Specific Outcome

The implementation and evaluation of the Competitive Ensemble Deep Learning (CEDL) model yielded several noteworthy outcomes across both structured and unstructured healthcare datasets:

1) **Improved Classification Accuracy:**
    - The CEDL model demonstrated a significant increase in classification accuracy compared to individual deep learning models. For instance, in the heart disease dataset, the CEDL model achieved a classification accuracy of 93%, compared to 83% using traditional deep learning models. Similarly, in the Breast Cancer dataset, the model reached an accuracy of 99%, highlighting its superior performance.
2) **Effective Model Selection:**
    - The competitive nature of the ensemble learning process ensured that only the best-performing models were selected for the final ensemble. This approach led to the exclusion of weaker models (e.g., SGD in the heart disease dataset), thereby preventing them from diminishing the overall performance of the ensemble.
3) **Robust Performance Across Data Types:**
    - The CEDL model proved to be highly adaptable, achieving high accuracy across different types of healthcare data. It handled structured datasets like clinical records with great efficiency, as well as unstructured datasets such as Twitter sentiment data, where it achieved an accuracy of 95% on the Diabetes Twitter dataset.
4) **Enhanced Multi-Label Classification:**
    - In unstructured data analysis, the CEDL model outperformed traditional models in multi-label classification tasks. The model's ability to handle complex text data, such as the COVID-19 Twitter dataset, resulted in an accuracy of 93%, demonstrating its effectiveness in understanding and classifying diverse sentiments within healthcare-related social media data.
5) **Reduced Computational Overhead:**
    - By selectively integrating only the most effective models into the ensemble, the CEDL model reduced unnecessary computational overhead, which is often associated with traditional ensemble methods that include all models regardless of their individual performance.
6) **Scalability and Versatility:**
    - The CEDL model showed promising scalability across datasets of varying sizes and complexities. Its ability to adapt to different optimizers

and model architectures makes it a versatile tool for a wide range of healthcare data analysis tasks.

7) Practical Application Potential:

- The outcomes suggest that the CEDL model could be effectively applied in real-world healthcare settings for tasks such as disease diagnosis, patient outcome prediction, and public health monitoring through social media analysis.

These specific outcomes underline the efficacy of the CEDL approach in improving the accuracy, efficiency, and applicability of deep learning models in healthcare data analysis, making it a valuable contribution to the field.

Figure 3

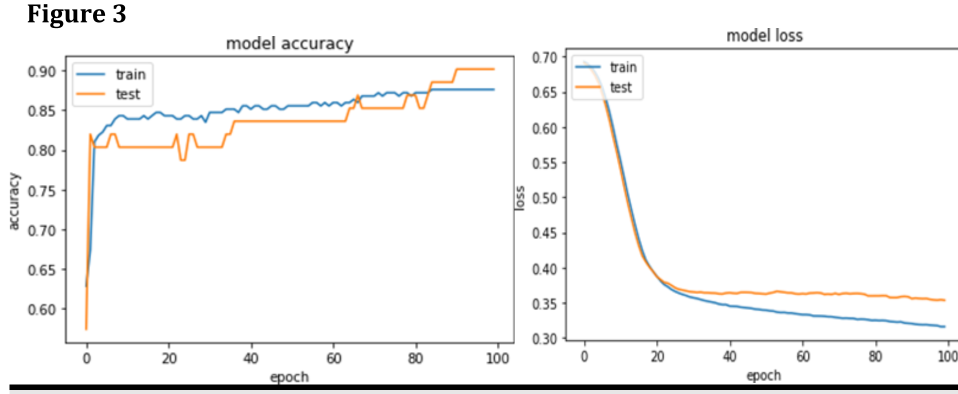

Figure 3 Training and Testing Accuracy, Loss of Proposed Work for Heart Disease Dataset

Figure 4

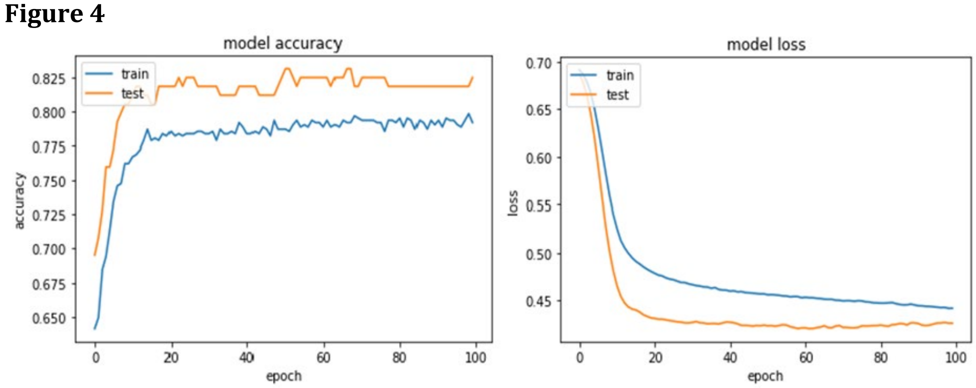

Figure 4 Training and Testing Accuracy, Loss of Proposed Work for Pima Dataset

Figure 5

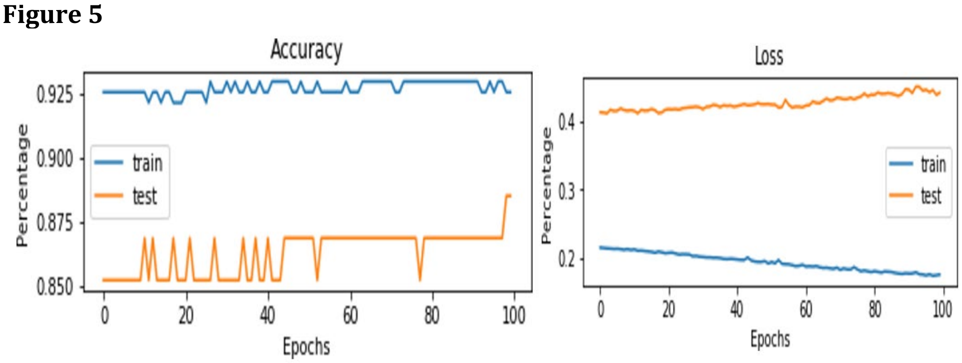

Figure 5 Training and Testing Accuracy, Loss of Proposed Work for Clinical Heart Disease Dataset

Figure 6

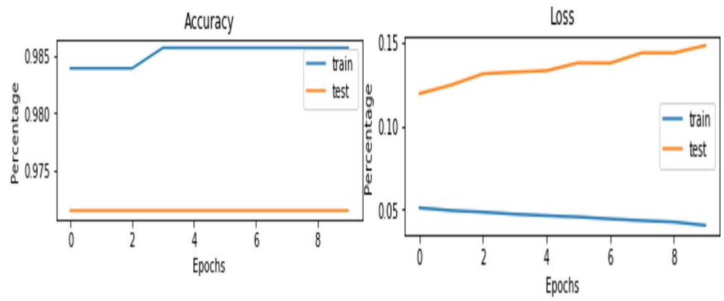

Figure 6 Training and Testing Accuracy, Loss of Proposed Work for Breast Cancer (Original) Dataset

Figure 7

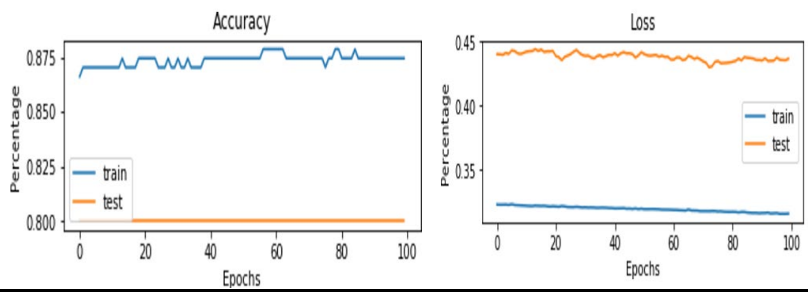

Figure 7 Training and Testing Accuracy, Loss of Proposed Work for Breast Cancer Coimbra Dataset

Figure 8

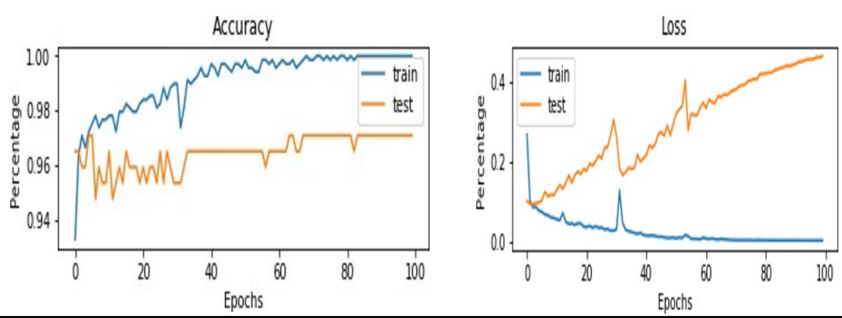

Figure 8 Training and Testing Accuracy, Loss of Proposed Work for Cervical Cancer Dataset

Figure 9

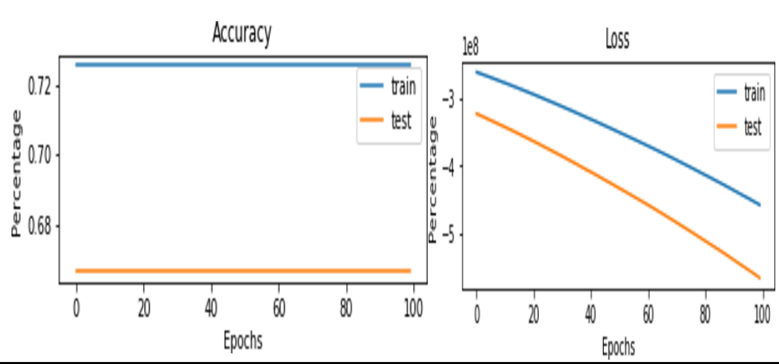

Figure 9 Training and Testing Accuracy, Loss of Proposed Work for Indian Liver Dataset

Figure 10

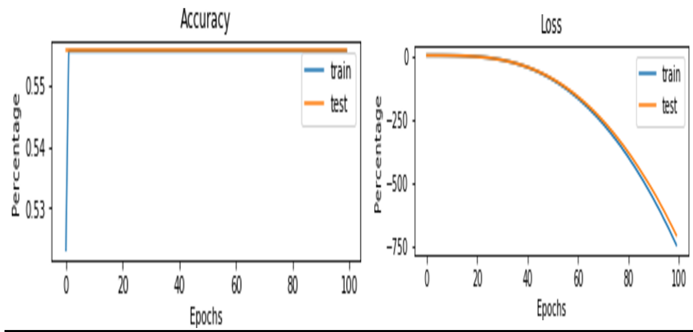

Figure 10 Training and Testing Accuracy, Loss of Proposed Work for Statlog Dataset

Figure 11

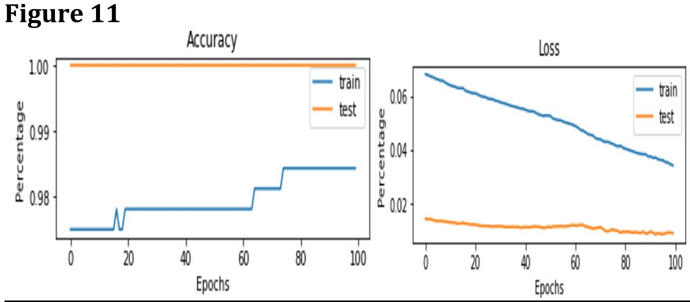

Figure 11 Training and Testing Accuracy, Loss of Proposed Work for Kidney Dataset

Figure 12

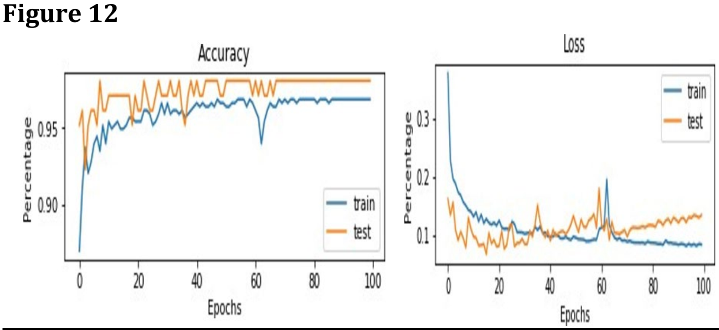

Figure 12 Training and Testing Accuracy, Loss of Proposed Work for Early Diabetes Dataset

Figure 13

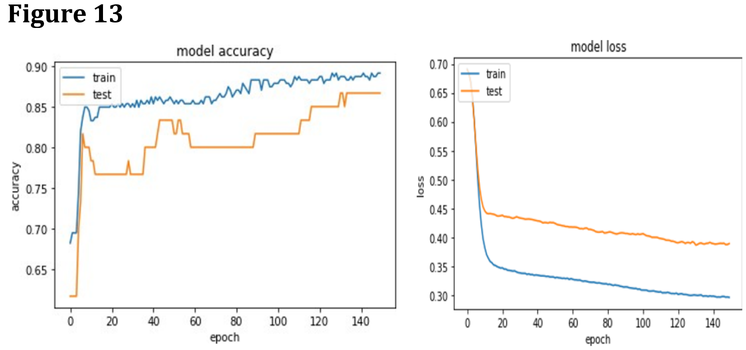

Figure 13 Training and Testing Accuracy, Loss of Proposed Work for Diabetes 130 US Hospital Dataset

Figure 3 to 13 illustrates training and testing accuracy for a structured healthcare dataset. For 100 epochs, the results are plotted on a graph using the proposed CEDL technique. The loss percentage of the model for each dataset is represented in the graph. The value increases and decreases based on the training and testing data. The dataset having very low instances receives low classification accuracy, whereas, for the large number of instances, the proposed work is much better.

6. CONCLUSION

The rapid growth of healthcare data, both structured and unstructured, presents significant challenges in data analysis and interpretation, particularly when traditional machine learning methods fall short in handling such complexity. This study introduced the Competitive Ensemble Deep Learning (CEDL) model as a novel approach to address these challenges, aiming to enhance classification accuracy and efficiency in healthcare data analysis. The CEDL model demonstrated its effectiveness across various healthcare datasets, significantly outperforming traditional deep learning models and ensemble methods. By selectively integrating only the best-performing models into the ensemble, the CEDL approach avoided the common pitfall of traditional ensembles, where weaker models can dilute overall performance. This selective process ensured that the final model ensemble was both robust and optimized for high accuracy. For structured healthcare datasets, such as those related to heart disease, diabetes, and breast cancer, the CEDL model consistently delivered higher accuracy rates than standalone deep learning models. For example, in the heart disease dataset, the CEDL model achieved an accuracy of 93%, significantly better than the 83% accuracy achieved by traditional deep learning approaches. The model also excelled in handling unstructured data, such as sentiment analysis from healthcare-related Twitter data, where it achieved an accuracy of 95% in the Diabetes Twitter dataset, demonstrating its capability to process and analyze complex text data effectively. The key strength of the CEDL model lies in its competitive selection mechanism, which ensures that only the most effective models contribute to the final ensemble. This approach not only improves classification accuracy but also reduces computational overhead by eliminating the need to include all models in the ensemble. Additionally, the CEDL model's flexibility in adapting to various types of data, from structured clinical records to unstructured social media posts, highlights its versatility and practical applicability in real-world healthcare scenarios. While the CEDL model demonstrated impressive results, it is not without limitations. One of the primary challenges is the computational complexity involved in training and evaluating multiple deep learning models, particularly for large-scale datasets. Although the model reduces unnecessary computational burden by excluding weaker models, the initial training phase still requires substantial computational resources. Additionally, the CEDL model's performance depends on the selection of optimizers and model architectures, which may require extensive experimentation to fine-tune for different datasets. The promising results of the CEDL model open up several avenues for future research. One potential direction is to further optimize the model's computational efficiency, making it more scalable for large datasets and real-time applications. Another area for exploration is the application of CEDL to other domains beyond healthcare, such as finance, marketing, and environmental monitoring, where complex data analysis is crucial. Additionally, integrating more advanced deep learning techniques, such as transfer learning and reinforcement learning, with the CEDL framework could further enhance its performance and adaptability. In conclusion, the CEDL model represents a significant advancement in healthcare data analysis, offering a robust and scalable solution for extracting meaningful insights from complex datasets. By leveraging the strengths of competitive ensemble learning, this model provides a powerful tool for improving diagnostic accuracy, patient outcomes, and overall healthcare management. As the volume and complexity of healthcare data continue to grow, approaches like CEDL will be increasingly important in ensuring that data-driven insights can effectively inform clinical decisions and public health strategies.

CONFLICT OF INTERESTS

None.

ACKNOWLEDGMENTS

None.

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