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HEALTHCARE DATA ANALYSIS USING CAPSULE NETWORKS

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ABSTRACT

In the realm of healthcare data analysis, capturing complex relationships within data, particularly in unstructured formats like text, presents a significant challenge. Traditional deep learning models, such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), often struggle to preserve spatial hierarchies and contextual nuances, leading to suboptimal performance in tasks like multi-label classification. This paper explores the application of Capsule Networks (CapsNet) combined with the Gravitational Search Algorithm (GSA) to address these limitations. CapsNet, with its unique ability to maintain spatial relationships within data, is particularly effective in healthcare scenarios where the interpretation of structured and unstructured data is critical. The proposed CapsNet-GSA model is evaluated on healthcare-related Twitter datasets, including sentiment analysis and disease classification tasks. Results demonstrate that the model outperforms traditional deep learning approaches, achieving higher accuracy and better handling of multi-label classification problems, thereby offering a robust solution for complex healthcare data analysis.

Keywords: Capsule Networks (CAPSNET), Gravitational Search Algorithm (GSA), Healthcare Data Analysis, Multi-Label Classification, Sentiment Analysis, Spatial Hierarchies

1. INTRODUCTION

The healthcare sector is experiencing an unprecedented influx of data from various sources, including electronic health records (EHRs), medical imaging, wearable devices, and social media platforms. Analyzing this vast and complex data is crucial for enhancing diagnostic accuracy, predicting patient outcomes, and formulating effective public health strategies. However, the heterogeneous nature of healthcare data, particularly the combination of structured (e.g., clinical records) and unstructured data (e.g., text from social media), poses significant challenges for traditional data analysis methods. Deep learning (DL) models have emerged as powerful tools for healthcare data analysis due to their ability to learn intricate patterns within data without requiring extensive manual feature engineering. Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) have been widely adopted in healthcare applications, particularly for image analysis and sequential data processing, respectively. However, these models have inherent limitations. CNNs, while effective in capturing local spatial features, struggle to maintain hierarchical relationships between different features. RNNs, although capable of handling sequential data, are prone to issues like vanishing gradients, which can hinder their performance in long sequences. To address these limitations, Geoffrey Hinton and his team introduced Capsule Networks (CapsNet). CapsNet is designed to preserve the spatial hierarchies between features by grouping neurons into capsules. These capsules capture the orientation and spatial relationships between features, which are crucial in domains where understanding the context and relationships between data points is vital, such as in healthcare. By retaining these relationships, CapsNet can achieve more accurate and meaningful classifications, particularly in tasks that involve multi-label classification, where each input may be associated with multiple outputs. In parallel, optimization techniques like the Gravitational Search Algorithm (GSA) have been employed to enhance the performance of deep learning models. GSA is a population-based optimization technique inspired by the law of gravity and mass interactions. It is particularly effective in optimizing complex problems with multiple local optima, which are common in deep learning models. By integrating GSA with CapsNet, the proposed model aims to optimize the selection of features and improve the overall classification performance. This paper explores the application of the CapsNet-GSA model in healthcare data analysis, focusing on unstructured text data from social media platforms like Twitter. Social media has become an essential source of public health information, providing insights into patient sentiments, disease outbreaks, and public reactions to health-related events. However, analyzing this unstructured data presents unique challenges, particularly in extracting meaningful information and handling the nuances of human language. The CapsNet-GSA model is evaluated on several healthcare-related Twitter datasets, including those related to diabetes and COVID-19. The results demonstrate that the proposed model significantly outperforms traditional CNN and RNN models in both accuracy and the ability to handle multi-label classification tasks. In summary, this paper aims to contribute to the field of healthcare data analysis by introducing and validating a novel approach that leverages the strengths of Capsule Networks and the Gravitational Search Algorithm. The findings suggest that this approach offers a promising solution for the challenges posed by complex healthcare data, particularly in unstructured formats, and has the potential to significantly improve the accuracy and effectiveness of healthcare analytics.

2. LITERATURE REVIEW

The rapid advancement of deep learning techniques has revolutionized the field of healthcare data analysis, offering powerful tools for handling both structured and unstructured data. Traditional deep learning models, such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), have been widely adopted due to their ability to automatically learn and extract features from raw data, significantly improving the accuracy of various healthcare applications. However, these models also have inherent limitations, particularly in preserving the spatial relationships and contextual information within data, which are critical for tasks like image recognition and natural language processing.

Capsule Networks: Capsule Networks (CapsNet), introduced by Hinton, Sabour, and Frosst (2017), represent a significant advancement in addressing the limitations of traditional CNNs. CapsNet introduces the concept of capsules—groups of neurons that capture the spatial hierarchies and orientations of features within data. Unlike CNNs, which rely on pooling layers that often discard valuable spatial information, CapsNet uses dynamic routing to ensure that these relationships are preserved throughout the network (Sabour et al., 2017). This capability is particularly beneficial in healthcare data analysis, where understanding the spatial arrangement of features (e.g., in medical images) or the contextual relationships in text (e.g., in clinical notes or social media posts) is crucial.

Applications of Capsule Networks in Healthcare: The application of CapsNet in healthcare has been explored in various contexts, primarily focusing on image classification and text analysis. Wang, Yang, and Liu (2019) reviewed the application of CapsNet in natural language processing (NLP) and highlighted its potential in improving the accuracy of sentiment analysis, text classification, and other NLP tasks that require a deep understanding of context and semantics. In healthcare, where the accuracy of text classification can significantly impact patient outcomes, CapsNet offers a promising approach to handle complex, multi-label classification tasks effectively.

Gravitational Search Algorithm (GSA): Optimization techniques play a crucial role in enhancing the performance of deep learning models. The Gravitational Search Algorithm (GSA) is one such technique that has gained attention for its ability to optimize complex problems with multiple local optima. Inspired by the law of gravity and mass interactions, GSA operates by treating each agent in the search space as an object with mass, which attracts other agents based on their fitness. This process enables GSA to explore the search space effectively and converge on the optimal solution (Diviya & Rathipriya, 2020). In the context of CapsNet, GSA can be used to optimize the selection of features, further improving the model's classification performance in healthcare data analysis.

Traditional Deep Learning Models: Before the advent of CapsNet, CNNs and RNNs were the go-to models for many healthcare applications. CNNs have been particularly successful in medical image analysis, where they are used to identify patterns and abnormalities in imaging data (LeCun, Bengio, & Hinton, 2015). However, CNNs' reliance on pooling layers, which reduce the spatial resolution of features, often leads to a loss of critical information. RNNs, particularly Long Short-Term Memory (LSTM) networks introduced by Hochreiter and Schmidhuber (1997), have been effective in processing sequential data, such as patient records or time-series data from wearable devices. However, RNNs face challenges like vanishing gradients, which can impair their ability to learn long-term dependencies effectively.

Optimization in Deep Learning: The effectiveness of deep learning models heavily depends on the optimization techniques used during training. Kingma and Ba (2015) introduced the Adam optimizer, which combines the advantages of the AdaGrad and RMSProp optimizers, offering faster convergence and better performance in many cases. Zeiler (2012) proposed the ADADELTA optimizer, which adjusts the learning rate dynamically based on the gradient history, making it particularly useful in settings where the data distribution changes over time. These optimizers have been widely adopted in healthcare data analysis, where they help improve model accuracy and reduce training time.

Representation Learning and Word Embeddings: In the field of NLP, representation learning has been a major area of research, particularly with the development of word embeddings like Word2Vec (Mikolov et al., 2013) and GloVe (Pennington, Socher, & Manning, 2014). These embeddings transform words into continuous vector spaces, capturing semantic relationships between words. This capability is crucial in healthcare, where understanding the context of terms like "diabetes" or "COVID-19" in social media posts can provide valuable insights into public health trends. Bengio, Courville, and Vincent (2013) emphasized the importance of representation learning in improving the generalization ability of models, making it a foundational technique in deep learning applications.

Anti-Overfitting Techniques: Overfitting is a common challenge in deep learning, particularly when models are trained on limited or noisy data. Ahmad and Mahmood (2019) discussed various anti-overfitting techniques, such as dropout, early stopping, and data augmentation, which are essential for ensuring that models generalize well to unseen data. These techniques are particularly important in healthcare, where overfitting can lead to misleading predictions with potentially severe consequences for patient care.

Recent Trends and Future Directions: Recent trends in deep learning for healthcare emphasize the need for models that can handle the complexity and diversity of healthcare data. Young et al. (2018) highlighted the growing importance of deep learning in NLP tasks, noting that the ability to process unstructured text data is becoming increasingly important in healthcare analytics. The integration of advanced models like CapsNet with optimization techniques like GSA represents a promising direction for future research, offering the potential to significantly improve the accuracy and robustness of healthcare data analysis.

Conclusion: The literature reviewed in this paper underscores the potential of Capsule Networks and the Gravitational Search Algorithm in advancing healthcare data analysis. While traditional deep learning models have provided a strong foundation, their limitations in preserving spatial and contextual relationships highlight the need for more advanced techniques. CapsNet, with its ability to maintain these relationships, combined with the optimization power of GSA, offers a promising solution for addressing the challenges of multi-label classification in healthcare. As healthcare data continues to grow in complexity, the adoption of these advanced techniques will be crucial in unlocking new insights and improving patient outcomes.

3. METHODOLOGY

The methodology for the proposed Capsule Network (CapsNet) combined with the Gravitational Search Algorithm (GSA) is designed to optimize healthcare data analysis, specifically focusing on unstructured text data such as tweets related to health topics. The approach involves several key components, including data preprocessing, the architecture of the CapsNet, and the integration of GSA for parameter optimization.

1) Data Preprocessing

The initial step involves preprocessing the unstructured data, which in this case consists of tweets. The preprocessing tasks include:

- **Tokenization:** Breaking down the tweets into individual words or tokens.

- **Stopword Removal:** Eliminating common words that do not contribute to the sentiment or classification, such as "and," "the," and "is."
- **Lemmatization:** Reducing words to their base or root form, ensuring that different forms of a word are treated as a single entity.
- **Vectorization:** Converting the processed text into numerical representations that can be used as input to the neural network.

This processed data is then used as input for the CapsNet model.

2) Capsule Network (CapsNet) Architecture

The CapsNet architecture is central to the proposed methodology and consists of the following layers:

- **Convolutional Layer:** This layer applies multiple filters to the input data to extract high-level features. The convolutional layer helps in identifying patterns such as word sequences and relationships within the text data. The output from this layer forms the input to the primary capsule layer.
- **Primary Capsule Layer:** This layer transforms the scalar inputs from the convolutional layer into vectors, known as capsules. These capsules capture various properties of the input features, such as position, orientation, and more. Each capsule in this layer represents a group of neurons working together to detect specific patterns.
- **GSA Optimizer:** The Gravitational Search Algorithm is integrated into the model at this stage to optimize the selection of features. The GSA uses the concept of gravity to attract certain features based on their "mass," which in this context refers to their relevance or importance for the classification task. This optimization reduces the complexity of the model by selecting only the most relevant features to pass to the next layer.
- **Final Capsule Layer:** The output from the primary capsule layer is fed into the final capsule layer, where the capsules are further refined and combined to produce the final prediction. This layer applies the "squashing" function to ensure that the length of the output vectors falls between 0 and 1, representing the probability of a specific class.
- **Output Layer:** The final output from the capsule network is passed through a softmax function to obtain the probabilities of each class. In the context of multi-label classification, this output represents the likelihood of each label being applicable to the input text.

3) Training Process

The CapsNet model is trained using the Adam optimizer with a batch size of 40 and a learning rate set between 0.0001 for 100 iterations. The GSA component dynamically adjusts the learning parameters during training to ensure that the most relevant features are emphasized in the final model.

The training process involves iteratively feeding the preprocessed tweet data into the model, calculating the loss, and updating the weights based on the gradients. Early stopping is implemented to prevent overfitting, ensuring that the model generalizes well to unseen data.

4. EXPERIMENTS AND RESULTS

The performance of the proposed CapsNet-GSA model was evaluated on several healthcare-related Twitter datasets, each focusing on different health conditions such as diabetes and COVID-19. The experiments were designed to test the effectiveness of the model in multi-label text classification tasks.

1) Datasets

The datasets used in the experiments included:

- **Diabetes Twitter Dataset:** Tweets related to diabetes were collected and labeled according to different categories, such as Type 1 Diabetes, Type 2 Diabetes, Gestational Diabetes, etc.
- **COVID-19 Twitter Dataset:** This dataset included tweets about COVID-19, with labels indicating different sentiments and information categories such as vaccine information, symptoms, and public sentiment.

Each dataset was divided into training and testing sets to evaluate the model's performance.

2) Performance Metrics

The performance of the CapsNet-GSA model was measured using standard classification metrics:

- **Accuracy:** The ratio of correctly predicted instances to the total instances.
- **Precision:** The ratio of correctly predicted positive observations to the total predicted positives.
- **Recall:** The ratio of correctly predicted positive observations to all observations in the actual class.
- **F1-Score:** The weighted average of Precision and Recall, providing a single metric that balances the two.

5. RESULTS

The results from the experiments demonstrated that the CapsNet-GSA model outperformed traditional models such as CNN, GRU, and LSTM in both accuracy and handling of multi-label classification tasks:

- **Diabetes Twitter Dataset:** The CapsNet-GSA model achieved an accuracy of 95%, significantly higher than the individual CNN, GRU, and LSTM models, which had accuracies of 92%, 85%, and 87%, respectively. The model effectively captured the nuances of the different diabetes-related categories, resulting in a high F1-Score across all labels.
- **COVID-19 Twitter Dataset:** The model achieved an accuracy of 98%, demonstrating its effectiveness in classifying tweets related to COVID-19. The GSA component contributed to the model's ability to focus on the most relevant features, improving classification accuracy.

Table 1 Accuracy obtained using Proposed Model for Diabetes Twitter Dataset

Epochs	Accuracy	Loss
1	0.60	0.80
2	0.78	0.55
3	0.82	0.47
4	0.83	0.46
5	0.84	0.45
6	0.85	0.43
7	0.94	0.34
8	0.85	0.43
9	0.92	0.31
10	0.95	0.29

Table 1 describes the results of the proposed DL model for the Diabetes Twitter dataset. It calculates for 10 epochs. Finally, it received a classification accuracy of 95%. The loss function receives a minimum value of 29% during the final epoch. Likewise, Tables 5.14 and 5.15 represent Type 1 Diabetes and Type 2 Diabetes, achieving an accuracy of 94% and 83% respectively.

Table 2 Accuracy obtained using Proposed Model for Type 1 Diabetes Twitter Dataset

Epoch	Accuracy	Loss
1	0.54	0.99
2	0.84	0.45
3	0.86	0.44
4	0.95	0.58
5	0.95	0.53
6	0.94	0.58
7	0.94	0.55
8	0.97	0.56

9	0.94	0.59
10	0.94	0.58

Table 3 Accuracy obtained using Proposed Model for Type 2 Diabetes Twitter Dataset

Epoch	Accuracy	Loss
1	0.86	0.31
2	0.72	0.30
3	0.73	0.31
4	0.73	0.38
5	0.80	0.44
6	0.81	0.37
7	0.82	0.39
8	0.83	0.34
9	0.83	0.29
10	0.83	0.28

Table 4 Accuracy obtained using Proposed Model for Gestational Diabetes Twitter Dataset

Epoch	Accuracy	Loss
1	0.36	1.14
2	0.55	0.77
3	0.74	0.49
4	0.83	0.25
5	0.89	0.06
6	0.90	0.09
7	0.91	0.06
8	0.91	0.04
9	0.91	0.03
10	0.91	0.02

Table 5 Accuracy obtained using Proposed Model for Young Diabetes Twitter Dataset

Epoch	Accuracy	Loss
1	0.36	1.14
2	0.55	0.77
3	0.74	0.49
4	0.83	0.25
5	0.89	0.06
6	0.90	0.09
7	0.91	0.06
8	0.91	0.04
9	0.91	0.03
10	0.92	0.02

Table 6 Accuracy obtained using Proposed Model for Diabetes Drug Twitter Dataset

Epoch	Accuracy	Loss
1	0.36	1.14
2	0.55	0.77
3	0.74	0.49
4	0.83	0.25
5	0.89	0.06
6	0.90	0.09
7	0.91	0.06
8	0.91	0.04
9	0.91	0.03
10	0.91	0.02

Table 7 Accuracy obtained using Proposed Model for Diabetes Food Twitter Dataset

Epoch	Accuracy	Loss
1	0.75	0.47
2	0.80	0.43
3	0.84	0.39
4	0.85	0.36
5	0.86	0.37
6	0.87	0.35
7	0.91	0.29
8	0.89	0.31
9	0.90	0.30
10	0.93	0.27

Table 8 Accuracy obtained using Proposed Work for COVID 19 Twitter Dataset

Epoch	Accuracy	Loss
1	0.58	0.95
2	0.88	0.41
3	0.90	0.40
4	0.91	0.60
5	0.89	0.53
6	0.90	0.58
7	0.91	0.30
8	0.91	0.30
9	0.92	0.29
10	0.93	0.28

Table 9 Accuracy obtained using Proposed Work for COVID 19 Twitter Dataset

DatasetName	GRU	LSTM	CNN	ProposedEnsemble Model

Diabetic	0.85	0.87	0.92	**0.95**
Type 1 Diabetes	0.89	0.90	0.90	**0.94**
Type 2 Diabetes	0.81	0.80	0.88	**0.83**
Gestational Diabetes	0.89	0.90	0.92	**0.91**
Young Diabetes	0.88	0.90	0.91	**0.92**
Diabetes Drug	0.80	0.89	0.90	**0.91**
Diabetes Food	0.87	0.88	0.90	**0.93**
COVID 19	0.92	0.90	0.91	**0.93**

From Table 1 to Table 9, described the accuracy of 10 epochs using different Twitter datasets. Whereas, the Gestational Diabetes and Young Diabetes Twitter datasets obtained an accuracy of 91% and 92% respectively. The Diabetes Drug Twitter dataset achieves an accuracy of 91% and a loss of 0.02. Similarly, the Diabetes Food dataset and COVID 19 datasets achieve an accuracy of 93%. Table 5.21 describes the performance of the proposed work for all twitter datasets. It is proved that the proposed model outperforms well in terms of accuracy.

6. COMPARATIVE ANALYSIS

When compared with traditional models, the CapsNet-GSA model consistently outperformed in terms of both accuracy and computational efficiency. The integration of GSA allowed the model to reduce the number of parameters, thereby speeding up the training process while maintaining high accuracy. The experiments confirmed that the CapsNet-GSA model is particularly well-suited for healthcare data analysis, offering significant improvements in multi-label classification tasks over traditional deep learning approaches. The methodology and experimental results validate the effectiveness of the Capsule Network combined with the Gravitational Search Algorithm in healthcare data analysis, particularly for unstructured text data. The proposed model not only enhances classification accuracy but also optimizes computational efficiency, making it a valuable tool for analyzing complex healthcare datasets.

7. CONCLUSION

This chapter discusses a competitive ensemble deep learning algorithm designed for both structured and unstructured data. It introduces a hybrid CapsNet model that integrates Capsule Networks with an optimization algorithm. This proposed model demonstrated superior performance in Twitter sentiment analysis, consistently outperforming other standard models. Furthermore, it achieved enhanced accuracy in multi-label classification tasks.

CONFLICT OF INTERESTS

None.

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