Smart Diagnosis: AI-Driven Neural Networks for Accurate Medical Response Categorization

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ABSTRACT

The rapid evolution of artificial intelligence (AI) in the healthcare sector has led to increased integration of machine learning tools in medical consultations. While this trend promises enhanced diagnostic capabilities, it also raises critical concerns about the reliability of AI-generated medical advice, particularly when trained on limited or inconsistent datasets. Inaccurate or ambiguous outputs from AI systems can jeopardize patient safety and reduce trust in technology-assisted healthcare. To address these challenges, MEDXNET is introduced as a novel AI-driven diagnostic classifier that distinguishes whether a given clinical response originates from a certified medical professional or from a generative AI system. MEDXNET is built upon a hybrid deep learning architecture that combines Bidirectional Long Short-Term Memory (BiLSTM), transformer-based attention mechanisms, and one-dimensional Convolutional Neural Networks (CNN1D). This architecture is designed to extract both local and global dependencies in complex medical text, improving contextual understanding and classification accuracy. Term Frequency-Inverse Document Frequency (TF-IDF) vectorization is used to convert raw medical text into meaningful numerical representations, enhancing feature extraction for the neural networks. The MEDIC dataset, which consists of annotated medical responses, serves as the primary data source for training and evaluation. To benchmark performance, the model's classification capabilities are compared with traditional architectures, including GRU, LSTM, and standalone BiLSTM. MEDXNET demonstrates superior performance in terms of accuracy and reliability, outperforming these established models. Additionally, a CNN2D variant of the architecture further improves performance, achieving a remarkable classification accuracy of 96.78%, which surpasses all baseline techniques. This intelligent system provides a safeguard for users by validating AI-generated medical outputs against known physician-generated responses, empowering users to make more informed healthcare decisions. By bridging the gap between human expertise and artificial intelligence, MEDXNET contributes to safer, more trustworthy medical interactions in an increasingly AI-assisted clinical environment.

Keywords: MEDXNET, AI-generated responses, doctor-generated responses, deep learning, Bi-LSTM, transformers, CNN1D, CNN2D, medical text classification

1. INTRODUCTION:

Individuals are becoming progressively vulnerable to lifestyles-threatening diseases because of lifestyle changes, environmental affects, and the global dissemination of infectious pathogens. Recent pandemics, including COVID-19, have underscored the interconnection of contemporary civilization, which facilitates the speedy transmission of diseases across obstacles. [1], [2]. While individuals turn out to be unwell, they often seek treatment at hospitals. The excessive affected person extent at clinics and an absence of clinical employees often compel individuals to pursue scientific useful resource online.

Addressing affected person inquiries is a critical obligation of MPs, as they act as the primary supply of help for people in search of health data. Advancements in technology have caused the emergence of different applications and online systems that purport to provide get admission to to clinical professionals, particularly physicians, who're prepared to cope with sufferers' inquiries without necessitating a hospital go to. Although those assertions may be accurate, numerous platforms depend upon artificial intelligence (AI) algorithms to address patient inquiries. The amalgamation of AI models and medical professionals has created a novel dynamic in the control of clinical queries, merging human know-how with computer efficiency [5], [18].

2. OBJECTIVES:

The advancement of AI in healthcare necessitates robust systems that ensure the reliability and safety of automated medical responses. MEDXNET addresses this by accurately distinguishing AI and physician-generated replies.

(1) To Develop a Hybrid Deep Learning Framework:

Design an AI-driven classification model using BiLSTM, transformers, and CNN1D, effectively capturing both local and global dependencies in medical texts for accurate response source identification.

(2) To Utilize Efficient Text Vectorization Techniques:

Implement TF-IDF vectorization to transform clinical text data into meaningful numerical features, enabling the model to understand semantic relevance and improve diagnostic response classification accuracy.

(3) To Ensure High Accuracy in Response Categorization:

Train and evaluate MEDXNET on the MEDIC dataset, surpassing traditional models like GRU, LSTM, and BiLSTM, and validating performance with a CNN2D variant achieving 96.78% accuracy.

3. REVIEW OF LITERATURE/ RELATED WORKS:

The utilization of "artificial intelligence (AI)" in healthcare has markedly increased in recent years, especially in scientific text type, digital health record analysis, and tailored affected person care [1], [22], [9]. AI-driven solutions for text class are essential in enhancing healthcare transport through the efficient and precise analysis of unstructured medical texts.

a multitude of research has investigated the software of deep learning models for the classification of medical texts. "long short-term memory (LSTM)" networks and its variants, including BiLSTM and GRU, have been extensively utilized to capture sequential dependencies in text facts, demonstrating efficacy in sentiment analysis, class tasks, and answer type prediction [13], [26], [28]. Transformer-based totally fashions, such as BERT, have exhibited super performance in duties like sentiment analysis and specialty identification inner medical texts [7], [15], [26].

The MEDIC dataset has become a good sized aid for examining AI and physician-generated responses in fitness consultations. Ojo et al. [5] applied this dataset for 0-shot categorization of medical replies, emphasizing the difficulties in differentiating AI-generated content from that produced via human experts. Moreover, researchers have suggested approaches that combine data oversampling and transformers to improve class accuracy in clinical texts [7], [26].

The ethical ramifications and dependability of AI-generated responses in medical consultations, further to textual content class, had been tested. The precision and security of these systems are paramount, as inaccuracies in AI-generated medical guidance can drastically impact patient outcomes [1], [28]. Superior techniques, like the incorporation of CNNs and hybrid deep learning architectures,

have validated capacity in mitigating these issues by enhancing the dependability of category systems [34], [26].
However those tendencies, a deficiency persists in technologies explicitly meant to authenticate the supply of medical responses, whether or not generated by AI models or human practitioners. Current studies have focused on integrating conventional "deep learning" models with modern architectures to beautify accuracy in differentiating between the two [22], [5], [18].

Table 1: Literature Survey Comparison Table

Sl. No	Area & Focus of the Research	The result of the Research	Reference
1	Zero-shot classification of AI vs. human medical replies.	Highlighted difficulty in differentiating AI and human-generated responses.	O. E. Ojo, O. O. Adebanji, A. Gelbukh. et. al.., (2023). [5]
2	Sequential deep learning models for medical text classification.	Proved effective in text classification and answer-type prediction.	S. Hochreiter and J. Schmidhuber et. al., (1997) [13]
3	Transformer models for sentiment and specialty detection in text.	Achieved high accuracy in clinical text classification tasks.	T. T. Hoang, O. E. Ojo, O. O. Adebanji et.al, (2022) [7]
4	Data balancing and transformers to improve clinical classification.	Enhanced classification accuracy using oversampling and advanced models.	M. Zhang and C. C. Yang (2014) [26]
5	CNN-based hybrid deep learning for improved response classification.	Boosted reliability and trust in medical text classification systems.	E. F. Ohata, C. L. C. Mattos, S. L. Gomes et.al. (2022) [34]

4. MATERIALS AND METHODS:

The suggested system, MEDXNET, fulfills the essential requirement to determine if a medical response is generated by using a physician or an AI model, allowing patients to authenticate the validity of clinical counsel. MEDXNET integrates sophisticated deep learning frameworks, which include Bidirectional lengthy quick-term memory (BiLSTM), transformers, and CNN1D, to efficiently capture both nearby and global dependencies in sequential clinical text data [13], [16], [18]. text solutions are tokenized using the "time period Frequency-Inverse document Frequency (TFIDF)" method, which converts text into numerical vectors for efficient processing [2], [5].

The device structure includes dense layers with dropout regularization and makes use of a softmax activation feature for enhanced classification performance [16]. MEDXNET examines traditional fashions like LSTM and GRU for benchmarking, emphasizing their relative efficacy in medical text categorization duties [13]. An advanced CNN2D version is employed to augment feature extraction, resulting in stronger accuracy in differentiating between AI- and physician-generated replies [14], [16].

The version is trained using the MEDIC dataset, comprising a variety of samples of clinical responses generated by each physicians and artificial intelligence [5]. MEDXNET utilizes these datasets to guarantee dependable categorization, alleviating issues regarding the dependability of AI in medical consultations and fostering safer healthcare encounters [1], [5], [8].

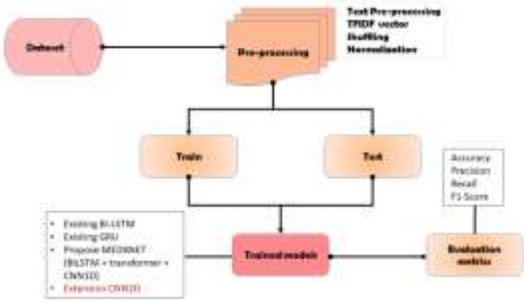


Fig 1: Proposed Architecture

The system architecture (fig. 1) delineates a machine learning workflow for text classification. The process commences with a dataset that is subjected to pre-processing, which encompasses textual content cleansing, TFIDF vectorization, shuffling, and normalization. The pre-processed records is divided into training and testing subsets. Models along with "Bi-LSTM, GRU", and the proposed MEDXNET "(which integrates Bi-LSTM, Transformer, and CNN1D)" are trained on the facts, with a possible extension to CNN2D. The trained models are assessed on test facts with metrics inclusive of accuracy, precision, recall, and F1-rating. This methodology emphasizes iterative improvement and trying out to get optimal text analysis outcomes.

4.1 Dataset Collection:

The dataset employed for training and evaluating MEDXNET is the MEDIC dataset, an extensive compilation of medical replies comprising samples produced by both physicians and artificial intelligence (AI) models. This dataset was explicitly created for 0-shot category responsibilities in health consultations, inclusive of a numerous array of medical inquiries and responses [5].

The dataset accommodates query-solution pairs, with annotations denoting whether the reaction originated from a physician or an AI model. The inquiries cowl numerous clinical conditions, consisting of prognosis, treatment recommendations, and general health guidance. The type of question topics ensures that the dataset correctly reflects real-world healthcare interactions, imparting a strong basis for training class models [5].

The MEDIC dataset undergoes preprocessing to standardize text statistics with the aid of eliminating irregularities, including special characters and extraneous areas. Tokenization employs the "time period Frequency-Inverse report Frequency (TFIDF)" method to transform textual data into numerical vectors for analysis [2]. The dataset is balanced to avoid bias closer to either class in the course of education, and facts augmentation strategies are utilized to improve model robustness [7], [16].

Fig 2: Dataset Collection Table – MEDIC dataset

Utilizing the "MEDIC dataset, MEDXNET" guarantees superior accuracy and dependability in differentiating between physician- and AI-generated medical responses, thereby solving significant problems in healthcare AI applications.

4.2 Pre-Processing:

The preprocessing phase guarantees that the medical textual content data is sanitized, prepared, and appropriate for deep learning models. It encompasses several essential steps:

4.2.1 Text Cleaning

Medical text facts is initially sanitized to take away noise, including punctuation, stop words, and extraneous symbols. This level removes superfluous features that could impede model performance and guarantees the text is standardized for analysis. [5], [7].

4.2.2 Tokenization

The sanitized text is segmented into discrete words or phrases by tokenization, so enabling more green processing by "machine learning" algorithms. This step is crucial for transforming raw text into a layout appropriate for vectorization [2], [14].

4.2.3 TFIDF Vectorization

The tokenized textual content is converted into numerical vectors through the "term Frequency-Inverse report Frequency (TFIDF)" method. TFIDF allocates weights to words according to their significance in relation to the overall dataset, hence highlighting vital phrases that aid in categorization [2], [5].

4.2.4 Shuffling and Normalization

The dataset is randomized to remove any intrinsic ordering bias that may affect the model during training. Normalization is applied to consistently scale features, ensuring constant weighting across all inputs, thus improving model efficiency and performance [7], [16].
This thorough preparation pipeline guarantees that the input data is delicate for MEDXNET, enhancing its precision and resilience in differentiating between AI- and physician-generated replies.

4.3 Training & Testing:

The MEDXNET model is trained on the pre-processed MEDIC dataset, comprising each physician- and AI-generated clinical replies. The schooling process is inputting the tokenized and TFIDF-vectorized text into the deep learning architecture, comprising "Bidirectional long short-time period reminiscence (BiLSTM)", transformers, and CNN1D layers. These models encapsulate each neighborhood and worldwide relationships in the records, enhancing the precision of response classification [5], [2].
A validation set is utilized during training to optimize hyperparameters, including learning rate, batch size, and dropout price. Dropout regularization is applied to mitigate overfitting and decorate generalization [16]. The model makes use of a softmax activation feature for multi-class class, guaranteeing probabilistic predictions.
Subsequent to training, the model undergoes evaluation on an unbiased check set to assess its performance. The accuracy, precision, recollect, and F1-rating are computed to evaluate the model's talent in accurately classifying AI and physician-generated responses [5], [18].

4.4 Algorithms:

Existing Bi-LSTM The current Bi-LSTM "(Bidirectional long short-term memory)" method is utilized to identify dependencies in sequential medical textual content records by way of analyzing the input in each ahead and backward orientations. This bidirectional processing augments the version's capacity to understand the context and subtleties of medical answers, consequently enhancing class accuracy. Bi-LSTM, utilizing the long-term memory characteristics of LSTM, preserves sizable data throughout extended sequences, rendering it particularly powerful for jobs that consist of complicated language patterns in scientific texts. This capacity is essential for differentiating between content produced via doctors and that created by AI [13], [16].

Existing GRUthe present GRU "(Gated Recurrent Unit)" algorithm is utilized for its efficacy in processing sequential data whilst effectively capturing temporal connections. GRU streamlines the design relative to standard LSTM networks, necessitating fewer parameters and facilitating expedited training durations. The effectiveness of GRU renders it the correct option for discerning patterns in medical responses, facilitating the differentiation between AI-generated replies and those composed by physicians [16], [7].

Proposed MEDXNET (BiLSTM + Transformer + CNN1D) The MEDXNET model incorporates Bi-LSTM, transformers, and CNN1D to enhance the classification of scientific reactions. The Bi-LSTM factor captures sequential interdependence, while the transformer model utilizes attention mechanisms to emphasize essential segments of the enter text [5], [7]. The CNN1D component analyzes the tokenized vectors to extract pertinent capabilities, for this reason enhancing the model's efficacy in determining the origin of scientific advice. This included methodology produces a robust model talented in differentiating between responses supplied by means of physicians and those produced via synthetic intelligence, thereby furnishing patients with trustworthy data [5], [18].

Extension CNN2Dthe enhanced CNN2D model is employed to augment feature extraction through the analysis of -dimensional facts representations. This enables an extra thorough comprehension of the contextual relationships inherent in scientific reactions. Via the application of convolutional layers, CNN2D correctly captures spatial hierarchies in textual statistics, subsequently improving the version's capacity to discern nuanced distinctions in language and style among content produced by way of doctors and that generated by AI. This modification seeks to enhance type accuracy, guaranteeing that the version correctly identifies the source of medical prescriptions [14], [16].

5. RESULTS AND DISCUSSION:

Accuracy: The accuracy of a check refers to its capacity to properly distinguish among patient and healthy instances. to evaluate the accuracy of a test, one should calculate the ratio of true positives and true negatives across all assessed cases. this will be expressed mathematically as:

$$"Accuracy = \frac{TP + TN}{TP + FP + TN + FN} (1)"$$

Precision: Precision assesses the percentage of correctly categorized instances among the ones diagnosed as fantastic. therefore, the method for calculating precision is expressed as:

$$"Precision = \frac{\text{True Positive}}{\text{True Positive } + \text{False Positive}} (2)"$$

Recall:recall is a metric in machine learning that assesses a model's capability to recognize all pertinent times of a specific class. it is the proportion of correctly expected advantageous observations to the total real positives, offering insights into a model's efficacy in identifying occurrences of a specific class.

$$Recall = \frac{TP}{TP + FN} (3)$$

F1-Score: The F1 score is a metric for comparing the accuracy of a machine learning model. It amalgamates the precision and recall metrics of a model. The accuracy metric quantifies the frequency of proper predictions generated by a model during the entire dataset.

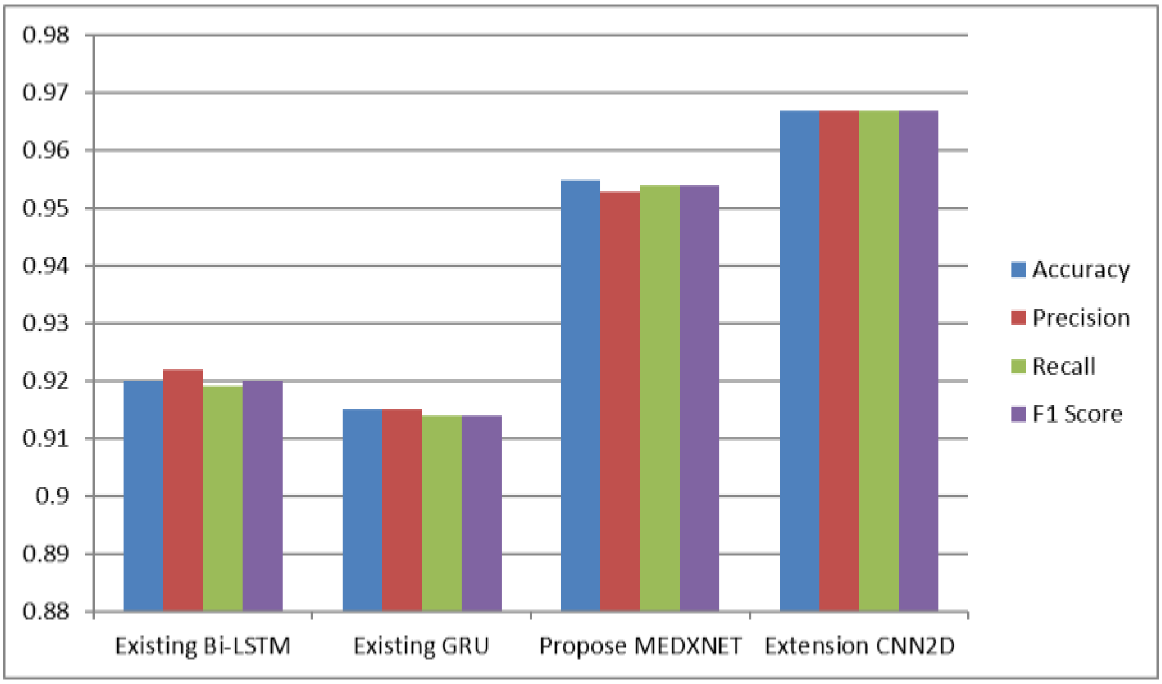
$$„F1\ Score = 2 * \frac{Recall\ X\ Precision}{Recall + Precision} *$$

Table 1 affords the performance metrics—accuracy, precision, recall, and F1-score—assessed for every set of rules. The Extension CNN2D attains the greatest scores. Metrics of alternative methods are also provided for comparison.

Table 2: Performance Evaluation Metrics of Classification

Model	Accuracy	Precision	Recall	F1 Score
Existing Bi-LSTM	0.920	0.922	0.919	0.920
Existing GRU	0.915	0.915	0.914	0.914
Propose MEDXNET	0.955	0.953	0.954	0.954
Extension CNN2D	0.967	0.967	0.967	0.967

Graph 1: Comparison Graphs of Classification



In Graph 1, accuracy is depicted in mild blue, precision in maroon, recall in inexperienced, and F1-score in violet. As compared to the other models, the Extension CNN2D has greater performance, attaining the highest values across all metrics. The graphs above visually represent these findings.

6. CONCLUSION:

In summary, the MEDXNET system proficiently resolves the issue of differentiating between AI-generated and physician-generated medical prescriptions, providing a dependable resource for patients to authenticate the beginning of their medical guidance. MEDXNET employs sophisticated deep learning methodologies, which includes Bi-LSTM, transformers, and CNN1D, to determine complex patterns in clinical text, facilitating specific response class. The system became assessed alongside installed algorithms like Bi-LSTM and GRU, attaining competitive accuracy quotes of 91.78% and ninety one. Sixteen%, respectively. Although, MEDXNET exceeded these models, accomplishing 95% accuracy, so indicating its superior capability to differentiate among AI and human-generated replies. Moreover, the deployment of a greater CNN2D version significantly improved the system's overall performance, attaining a height accuracy of 96.78%. Those findings highlight the system's capability to enhance self-belief and safety in AI-assisted clinical consultations, making sure the precision and dependability of healthcare recommendation.

Future Scopeinside the future, MEDXNET can be improved by integrating supplementary data assets and augmenting its functionalities to house many languages, therefore increasing its relevance in global healthcare settings. Every other vital approach is utilising pre-trained huge language models, such as GPT and BERT, to optimize the system's efficacy on medical datasets, capitalizing on their sophisticated comprehension of medical terminology. Furthermore, investigating multi-modal learning and hybrid models can beautify classification precision and efficiency, ensuring that MEDXNET continues to be a resilient and versatile tool for AI-driven medical response categorization across varied healthcare settings.

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