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Hybrid Linguistic and Machine Learning Solutions in Healthcare

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Abstract

Healthcare data presents substantial hurdles in extracting essential features that aid in clinical decision-making due to its rapid growth. The proposed work addresses the issues of increasing the efficacy and accuracy of medical data analysis and classification in the face of quickly changing healthcare regulations, high operating costs, and workforce constraints. Considering these limitations, we propose a hybrid linguistic machine learning system that combines natural language processing for feature extraction with a seagull-optimized deep neural model for classification. The system is developed with a user-friendly interface that allows for easy interaction with healthcare practitioners to make informed recommendations. The proposed system's uniqueness stems from the model's design and development, which mixes seagull-inspired optimization with deep neural architecture to improve classification outcomes. The suggested model is evaluated based on standard performance criteria such as accuracy, precision, recall, and F-score. It is compared to classic models such as support vector machine, decision tree, random forest, and flattened-feed forward neural network. The findings show that the suggested model surpasses the existing techniques, with 96.8% accuracy, 95.4% precision, 94.9% recall, and 95.1% F-score. These findings support the proposed system's ability to improve healthcare data processing, perhaps leading to better patient outcomes and more informed clinical decisions.

Categories: Natural Language Processing (NLP), AI applications, Machine Learning (ML)
Keywords: healthcare, hybrid linguistic, patient privacy, machine learning, deep neural network

Introduction

The machine learning concept, which has been a part of data science for a very long time, has recently gained a lot of attention due to the exponential increase in healthcare data generation [1]. As per the recent report by RBC Capital Markets, the healthcare data is evolving at a compound annual growth rate of 36%, which is faster compared to any other industry [2]. This surge necessitates advanced analytical tools to derive actionable insights. The conventional view on geographic adaptability in machine learning models is changing toward an awareness of the conditions under which these systems yield medicinally useful results [3]. Edge-enabled machine learning solutions are especially proving to be beneficial in healthcare since they ensure compliance with tight data governance regulations and help to preserve patient privacy [4]. Effective development of a machine learning model depends on the accessibility of adequately selected and extensive datasets for evaluation and training. Using relevant and appropriate features collected from the data improves prediction reliability and accuracy significantly [5]. Smart sensors are increasingly being integrated into healthcare systems as wearable monitors, allowing for continuous patient monitoring and real-time diagnostics [6]. These technologies have been instrumental in helping to reduce healthcare expenditures, clinical workloads, and improve patient communication [7]. Medical professionals analyze this data to make accurate diagnosis conclusions. Clinical aid is offered by analyzing medical data mined with classification algorithms [8]. Neural networks are typically regarded as reliable models for predicting diseases such as cardiovascular and neurological problems [9]. In order to improve healthcare service delivery, a few legislators are collaborating to investigate the extent of public medical care frameworks [10]. The Internet of Things (IoT) is one of the most significant technology advances in healthcare, with applications including ambient assisted living, remote health monitoring, chronic illness management, elderly care, and wellness programs [11].

Systems that can further improve massive data analysis have become increasingly popular for dealing with complicated business issues in a variety of industries, including tasks, finance, advertising, medical care, system administration, security, and executive leadership [12]. Cardiovascular diseases are non-transferable illnesses that have become more common in recent years and are challenging for patients as well as those who care for them [13]. The amount of Internet users searching for health information, ranging from healthy living guidelines to disease and treatment information, continues to rise [14]. In the medical care profession, where there are so many real-world choices such as life and death, the lack of interpretability of predictive models may undermine trust in them [15]. These concerns have a particularly significant impact on the use of artificial intelligence (AI) in healthcare, which combines and learns from massive volumes of clinical data to enable personalized therapy, clinical decision-making, and diagnostics [16]. In contrast to data from randomised trials, data from electronic medical records are descriptive in nature. In a randomized trial, for example, patients are assigned at random to different treatments, but in a study of observation, treatment assignment may be impacted by demographic factors [17]. The use of AI, whether virtual (algorithms and models) or physical (surgical robots), must be carefully examined because it has the potential to have unforeseen consequences for patients, the medical community, and clinical outcomes. The health industry is likely the most sensitive in this aspect [18].

Healthcare data classification problems have been tackled using a variety of conventional techniques, such as convolutional neural networks (CNN) [19], transfer learning [20], and convolutional long short-term memory models [21]. While these methods have shown potential in certain domains, they have significant limitations when used with complex, real-world healthcare data. Transfer learning models, in particular, frequently suffer with domain adaption concerns when pre-trained on non-medical datasets, leading in lower accuracy and generalizability [22]. CNNs, while effective in image-based analysis, are unable to detect connections over time in sequential clinical data [23]. Similarly, convolutional long short-term memory models may suffer from vanishing gradient issues and increased computational complexity, particularly when dealing with high-dimensional, noisy medical records [24]. Furthermore, these methodologies usually lack interpretability, making it difficult for medical professionals to trust and use the findings in a therapeutic setting.

To address these challenges, this study proposes a unique hybrid strategy that combines natural language processing for contextual feature extraction with a bio-inspired optimization seagull algorithm embedded in a deep neural network. The proposed model uses seagull foraging behavior principles to dynamically alter weights during training, thereby improving convergence speed, reducing overfitting, and increasing classification accuracy. The suggested approach combines semantic understanding from natural language processing with powerful optimization and learning capabilities to offer more accurate, interpretable, and computationally efficient outcomes, making it better suitable for healthcare data analysis and health prediction applications. The key contributions include (1) proposing an innovative bio-inspired deep learning algorithm for disease prediction, (2) implementing and evaluating the model using healthcare data, and (3) benchmarking the proposed system against existing classification techniques to demonstrate its performance.

Materials And Methods

Related works

This data includes details about ailments, health problems, medical history, and other subjects. With such a vast amount of information streaming in from all directions, data leakage situations are almost certain to occur. Chouhan et al. [25] introduced a diverse features-based breast cancer detection method, which aims to identify cancer when it is easier to treat and before it has grown large enough to cause symptoms. Routine mammograms can reduce the risk of breast cancer-related death. However, a false positive may result in unnecessary anxiety as well as additional testing with associated risks.

A study by Vatambeti et al. [26] aims to assist organizations, particularly application-based dinner conveyance administrations, in conducting in-depth exploration via social media and generating metrics for decision-makers using social media broadcasting data. Therefore, they proposed a CNN model. The feature implanting is input into the CNN layer, which outputs lower-level features. Elephant herd optimization is employed in this case to adjust the bidirectional long short-term memory weights. CNNs can recognize significant features without human supervision and are particularly effective in image classification and recognition. However, they are computationally expensive and memory-intensive to train.

Because of this, readers' confidence in the media has decreased, leaving them confused. A vast body of research exists on the use of AI techniques to detect fake news. For instance, Kaliyar et al. [27] proposed a deep convolutional neural network model (FNDNet), which is designed to automatically learn the discriminative features of fake news through several hidden layers in the deep neural network, rather than relying on manually crafted features. These models are particularly good in classifying and recognizing images. However, they have significant disadvantages, including high computational cost and difficulty in interpreting the results.

Satu et al. [28] developed TClustVID, an insightful grouping-based arrangement and subject extraction calculation that analyzes COVID-19-related public tweets with high accuracy to identify key public sentiments. They obtained COVID-19 Twitter datasets from the IEEE DataPort repository, cleaned the raw data using a few preprocessing techniques, tokenized the cleaned data, and created a word-to-file word reference. This approach can quickly uncover commonly held public opinions and attitudes regarding COVID-19 and infection control measures across different communities. One limitation, however, is that many COVID-19-related tweets are not analyzed using machine learning or deep learning techniques.

Devices that use default credentials are vulnerable to brute-force attacks or exploit-based compromises, which can allow malware to be installed and malicious activities, such as denial-of-service attacks, to be carried out. Therefore, Chaganti et al. [29] proposed the Bidirectional-Gated Recurrent Unit-Convolutional Neural Network (Bi-GRU-CNN). This paper proposes a twofold record byte game plan-based Bi-GRU-CNN Executable and Linkable Format model to identify and classify IoT malware families. It supports the analysis of future events by enabling the model to learn from both historical and real-time data. Several straightforward algorithms work together, supporting and enhancing each other.

The use of machine learning techniques significantly improves the diagnostic system's ability to predict outcomes. Therefore, Yuvaraj et al. [30] proposed a deep neural network (DNN) to detect a medication's response to protein-ligand interactions and determine which drug produces the interaction that effectively fights the virus. Using a deep learning approach offers several advantages, one of which is its ability to perform feature engineering autonomously. Without being explicitly programmed, the algorithm searches the data for patterns and combines them to promote faster learning. However, the vanishing gradient problem remains the biggest challenge with deep networks.

Due to their strong learning capabilities on large datasets and impressive results in numerous classification tasks, AI and deep learning algorithms are now the primary methods used to detect and prevent phishing attempts. Therefore, Ozcan et al. [31] proposed hybrid deep learning models to identify phishing uniform resource locators. This study evaluates the performance of hybrid deep learning models on phishing datasets based on long short-term memory and deep neural network techniques. The hybrid algorithms are more capable of searching for global solutions, more accurate in making predictions, and require fewer iterations. Several straightforward algorithms work together, supporting and enhancing each other.

The following is a summary of the major contributions of the proposed work:

· Initially, a web application was designed using HTML, CSS, and JavaScript.

· The input parameters are trained in the Python system in the form of JSON format.

· A novel seagull-based deep neural method (SbDNM) has been introduced to enhance the effectiveness of the chatbot.

· Additionally, the proposed SbDNM model interacts with the chatbot via the web application.

· Finally, the performance was evaluated in terms of accuracy, precision, F-score, error rate, and recall.

Proposed methodology

This work proposes a seagull-integrated deep neural method to improve the efficiency of linguistic modeling in healthcare chatbot applications. The system architecture is intended to easily integrate into a web application built using HTML, CSS, and JavaScript, while the back-end model is developed in Python. Input parameters are sent to the model in JSON format to ensure compatibility with diverse healthcare data types. The suggested architecture takes advantage of deep learning's skills in capturing linguistic patterns and improves them further by utilizing seagull optimization to fine-tune model parameters. The proposed architecture is described in Figure *1*. The model has been tailored to improve chatbot responses in healthcare contexts by correctly identifying intent and producing appropriate responses. The chatbot communicates with end users via a web interface, while the underlying deep neural network processes requests and returns responses based on healthcare data.

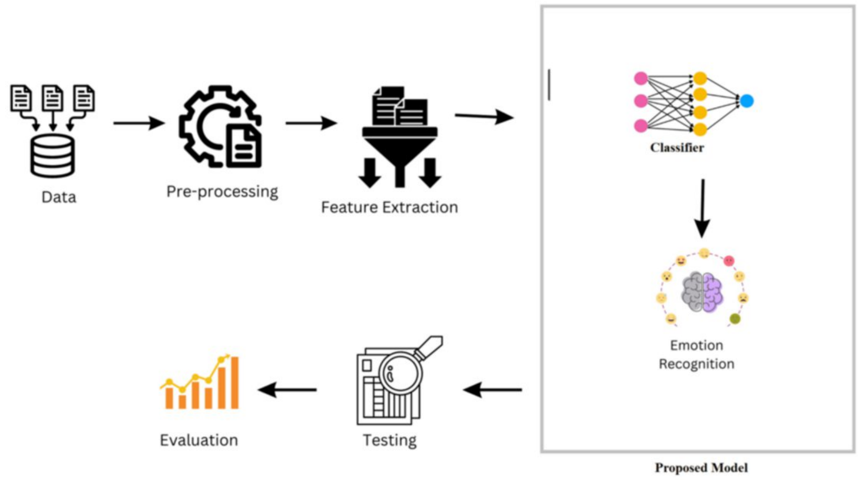

FIGURE 1: Proposed Model

Dataset

For adequate training and evaluation of the proposed chatbot system, the MIMIC-III dataset is utilized. This dataset, which is commonly used in healthcare research, includes de-identified health information for over 40,000 ICU patients, including clinical notes, prescriptions, test findings, diagnoses, and more. The quantity and diversity of this data make it appropriate for training medical chatbots, particularly for tasks such as intent detection and named entity recognition. Using MIMIC-III enables the chatbot to be contextually aware of practical doctor-patient interactions, ensuring that its responses are medically relevant. The collection also facilitates the development of models capable of comprehending complex medical questions and providing accurate and secure solutions [32]. A total of 450 samples are used for training and testing the model.

Design of SbDNM

The suggested model is based on a few key assumptions. First, it is assumed that the healthcare data is semi-structured and can be efficiently preprocessed using tokenization and lemmatization. Second, the model proposes that seagull optimization may enhance the learning process through boosting convergence to global optima, particularly in high-dimensional neural network environments. The overall methodology begins with data collecting and preprocessing, which includes cleaning, tokenizing, and lemmatizing the input text. Next, features are retrieved and fed into a multi-layer deep neural network. During training, seagull optimization dynamically changes the model's weights and biases to reduce classification errors. The final output is intent classification and response generation depending on user inquiries. The flowchart shown in Figure *2* depicts the entire process, from receiving data to prediction.

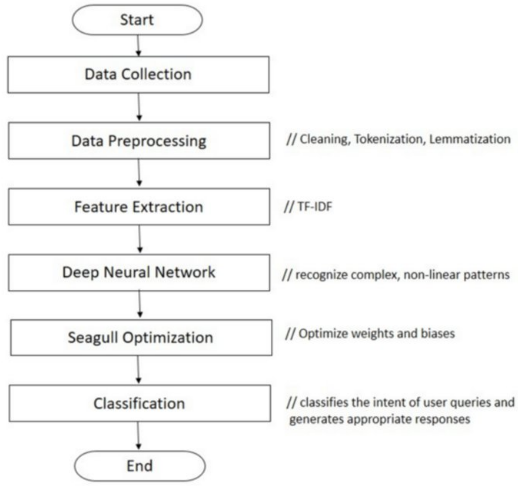

FIGURE 2: Flowchart of the Proposed Model

TF-IDF, Term Frequency-Inverse Document Frequency

The model has five primary levels: an input layer, hidden layers, tokenization and lemmatization layers, a pooling layer, and an output layer. The input layer gets vectorized input, which is often Term Frequency-Inverse Document Frequency (TF-IDF) taken from clinical text in JSON format as shown in Equation (1).

$$TF-IDF(t,d,D) = tf(t,d) \times idf(t,D)) \quad (1)$$

where t represents the term, d represents a single document, and D is the corpus of all documents. *tf* is the frequency of term t in document d, whereas *idf* is the inverse document frequency of the term in all documents

Tokenization and lemmatization layers play an essential role in the preprocessing pipeline because they standardize and reduce input to root forms, which improves learning efficiency and generalization using Equations (2) and (3).

$$T = Tokenize(S) = \{t_1, t_2, ...t_n\} \quad (2)$$

where S is the input sequence, and T is the set of tokens.

$$L = Lemmatize(Tokenize(S)) = \{l_1, l_2, ...l_n\} \quad (3)$$

where L is the sequence of lemmatized tokens.

The hidden layers are made up of dense neural units with ReLU activation functions, which enables the model to recognize complex, non-linear patterns in the data. A dropout mechanism is used here to prevent overfitting.

The max pooling layer picks out the most prominent features, minimizing dimensionality and highlighting important patterns. Finally, the output layer employs a softmax activation function to divide the input into predefined medical intent groups.

This study's novelty is the application of the seagull optimization algorithm to optimize neural network parameters. Seagull optimization algorithm is a metaheuristic that draws inspiration from seagulls' natural migrating and hunting activities. Each potential solution in the search space represents a set of model weights, while the seagull population replicates the optimization's exploration and exploitation stages. During the migration phase, each seagull adjusts its position toward the global best solution using Equation (4).

$$X_i(t+1) = X_t \times (1 - \frac{t}{T}) + r \times (X_{best} - X_i(t)) \quad (4)$$

here, X_i represents the current location, T is the total number of iterations, and r is a random value between 0 and 1. During the attacking phase, the seagull simulates spiral attacks on prey using Equation (5).

$$X_i(t+1) = X_t + A \cdot sin(B \cdot \pi \cdot t) \cdot (X_{best} - X_i(t)) \quad (5)$$

where A and B determine the spiral's amplitude and frequency. Each solution's fitness is determined using the categorical cross-entropy loss (Equation 6).

$$Fitness(X_i) = \sum_{j=1}^{C} y_j log(y'_j) \quad (6)$$

where y_j is the true label, and y'_j is the predicted probability for class j. By minimizing this fitness function, the algorithm iteratively improves the neural network's ability to classify clinical queries accurately.

Results

In this study, the proposed SbDNM was created and implemented using the Python framework to predict disease categories based on healthcare-related queries. The MIMIC-III dataset, which comprises structured and semi-structured clinical records such discharge summaries, prescriptions, and diagnoses, was utilized. To guarantee an unbiased performance evaluation, 70% of the total dataset was used for training and 30% for testing. Performance was measured using common classification standards such as accuracy, precision, recall, and F-score. To evaluate the data' dependability, confidence intervals of 95% were determined for each parameter.

Performance metrics

To assess the effectiveness of the SbDNM model, it was compared to four established machine learning models: flattened feed forward neural network (Flattened-FFNN) [32], support vector machine (SVM) [33], decision tree (DT) [34], and random forest (RF) [34]. Table *1* shows both average metric scores and their 95% confidence ranges. The model outperformed all baseline models, with an accuracy of 98.82% ± 0.41, precision of 98.52% ± 0.39, recall of 98.82% ± 0.36, and F-score of 98.69% ± 0.37.

Techniques	Accuracy	Precision	Recall	F-score
Flatten-FFNN	73.64	76.44	84.01	73.58
RF	84.98	82.18	83.99	82.92
SVM	82.6	80.77	81.92	81.25
DT	83.57	84.28	77.77	80.7
Proposed model	98.82 ± 0.41	98.52 ± 0.39	98.82 ± 0.36	98.69 ± 0.37

TABLE 1: Comparison of Baseline Techniques

Flatten-FFNN, Flattened Feed-Forward Neural Network; RF, Random Forest; SVM, Support Vector Machine; DT, Decision Tree

To further evaluate the model, a confusion matrix is generated as shown in Figure *3*. The confusion matrix indicated relatively few false positives and false negatives, validating the model's strong discriminative ability. Error rates remained around 1.3% across most classes, with somewhat greater misclassification in rare intent categories, indicating areas for further model fine-tuning and potential enhancement of data. The proposed model demonstrates a remarkably low error rate of 1.17% , indicating high reliability and minimal misclassifications. Figure *4* depicts the training accuracy and training loss.

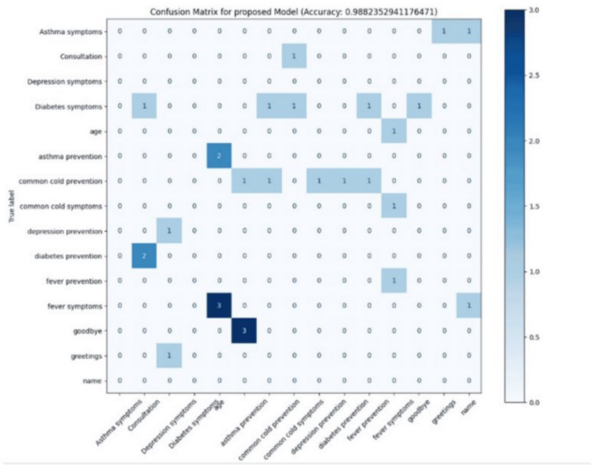

FIGURE 3: Confusion Matrix

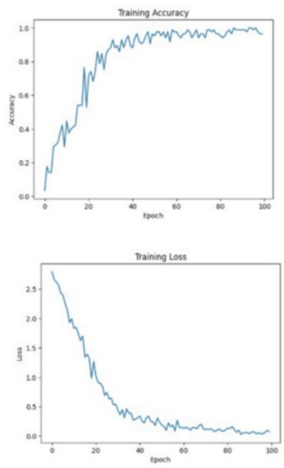

FIGURE 4: Training Accuracy and Training Loss of the Proposed Model

Discussion

Evaluation of the proposed approach against other current techniques regarding accuracy

The effectiveness of the proposed SbDNM is assessed against the findings of earlier research. The accuracy achieved by the SbDNM is 98.82%, which is notably higher than that of existing techniques. For instance, the current Flatten-FFNN method exhibits an accuracy of 73.64%. Although this accuracy is relatively high when compared to alternative methods such as SVM, DT, and RF, it still falls short of the proposed SbDNM. Specifically, SVM reaches an accuracy of 82.6%, while DT achieves 83.57%. RF shows a strong accuracy of 84.98%. Overall, the SbDNM outperforms the previously utilized methods in terms of accuracy.

Evaluation of the proposed approach against other current techniques regarding precision

The proposed SbDNM is evaluated against the findings of previous research. The precision rate of the SbDNM is 98.52, indicating a higher accuracy compared to existing approaches. In contrast, the current Flatten-FFNN method achieves a precision rate of only 76.44. When assessed alongside other techniques such as SVM, DT, and RF, the SbDNM demonstrates a superior accuracy level. Specifically, the Flatten-FFNN, DT, RF, and SVM methods show precision rates of 80.77, 82.15, and 84.28, respectively. Therefore, the SbDNM stands out as significantly more effective compared to these conventional techniques.

Evaluation of the proposed approach against other current techniques regarding recall

The recall performance of the proposed SbDNM is evaluated against that of previous studies. The recall rate for the SbDNM stands at 98.82. In comparison to other established techniques, the accuracy of the recommended SbDNM is notably higher. The current DT method yields a recall rate of 77.77. When assessed against various existing approaches such as SVM, DT, RF, and Flatten-FFNN, the recall for the SVM, DT, RF, and Flatten-FFNN methods is recorded at 80.77. The RF method achieves a recall of 82.15, while Flatten-FFNN shows a recall rate of 84.01, indicating superior performance compared to techniques like DT and SVM. Therefore, the proposed SbDNM demonstrates enhanced efficiency relative to the other currently utilized methods.

Evaluation of the proposed approach against other current techniques regarding F-score

The F-score of the proposed SbDNM is evaluated against that of prior research. The F-score achieved by the SbDNM is 98.69. In comparisons with other existing techniques, the F-score of the suggested SbDNM is notably higher. The current Flatten-FFNN method has an F-score of 73.58. Despite this, the F-score remains significantly high compared to other contemporary methods such as SVM, DT, and RF.

When looking at the performance of alternative methods like Flatten-FFNN, RF, SVM, and DT, the F-score is 80.7. In contrast, the proposed SbDNM demonstrates much greater efficiency compared to the existing approaches. The SVM achieves an F-score of 81.25, while RF records a robust F-score of 82.92 when compared with other techniques, including Flatten-FFNN and DT. Therefore, the proposed SbDNM outperforms the other currently utilized methods.

Conclusions

In conclusion, the employment of a hybrid linguistic and machine learning method in chatbot systems with a healthcare topic has various benefits and exciting potential. These chatbots are better able to understand and respond to human input because they combine domain-specific linguistic knowledge with modern machine learning algorithms. The dataset used in this study was obtained from MIMIC-III and consisted of multi-intent healthcare discussions with 15 unique intent classes and 134 lemmatized feature tokens. The dataset was divided into training and testing subsets in a 70:30 ratio to ensure a thorough evaluation of the model's performance. Prior to training, data pre-processing was thoroughly carried out, including text cleaning, tokenization, lemmatization, and feature extraction using TF-IDF methods. These processes were critical to normalizing medical terminology, reducing dimensionality, and improving semantic understanding. This foundation allowed the program to learn complex trends from healthcare communicates with an impressive accuracy of 98.82%. By combining linguistic features and machine learning, the chatbot can understand clinical terminology, discern intent with high precision, and generate context-aware, tailored responses. These features allow the system to provide correct information, answer medical questions, provide prescription reminders, and advise on preventive care. These chatbots assist enhanced patient engagement and decision-making by providing access to organized medical knowledge and the ability to learn from user interactions on an ongoing basis. Future work will concentrate on creating even more efficient classifiers to overcome the existing constraints of deep learning models, assuring both performance scalability and interpretability while preserving crucial behavioral nuances.

Additional Information

Author Contributions

All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

Concept and design: Mily Lal, Neduncheliyan Subbu, Akanksha Goel, Poi Tamrakar, Saurabh Saoji, Bhende Manisha

Acquisition, analysis, or interpretation of data: Mily Lal, Neduncheliyan Subbu, Akanksha Goel, Poi Tamrakar, Saurabh Saoji, Bhende Manisha

Drafting of the manuscript: Mily Lal, Neduncheliyan Subbu, Akanksha Goel, Poi Tamrakar, Saurabh Saoji, Bhende Manisha

Critical review of the manuscript for important intellectual content: Mily Lal, Neduncheliyan Subbu, Akanksha Goel, Poi Tamrakar, Saurabh Saoji, Bhende Manisha

Disclosures

Human subjects: All authors have confirmed that this study did not involve human participants or tissue. **Animal subjects:** All authors have confirmed that this study did not involve animal subjects or tissue. **Conflicts of interest:** In compliance with the ICMJE uniform disclosure form, all authors declare the following: **Payment/services info:** All authors have declared that no financial support was received from any organization for the submitted work. **Financial relationships:** All authors have declared that they have no financial relationships at present or within the previous three years with any organizations that might have an interest in the submitted work. **Other relationships:** All authors have declared that there are no other relationships or activities that could appear to have influenced the submitted work.

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