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Chatbot-based Rheumatoid Arthritis Management System using Adaptive Nested Dilated TCN for Classification and Recommendation with Response Prediction

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Abstract

Here, we introduce an AI-based system specifically developed for efficient rheumatoid arthritis (RA) diagnostics and patient management. Early RA diagnosis is important, as its symptomatological mimicry with different arthritis, and treatment of the disease requires an effective control. To address this limitation, we propose a system leveraging the ATG-LSMSA model to learn patient text data from online sources and generate clinically relevant responses. Finally, a feature consisting of symptoms is fed to an Adaptable Nested Dilated Temporal Convolution Network (AND-TCN) which classifies RA severity as low, medium or high. Tailored recommendations — the system based on its information will give you tips for dietary interventions and exercise suggestions. A Revised Arbitrary Variable WO (RAV-WO) algorithm is then proposed to optimize the parameters of several models, decrease prediction errors and enhance the classification performance. Using a chatbot-assisted framework would allow for ongoing surveillance of RA activity, quality of life, and level of functional impairment status with appropriate recommendations made as indicated. It is evaluated and also compared with the traditional methods to show that there are better results in terms of almost all the metrics. This single center, integrated AI strategy provides a pragmatic support for patient self-management, and could serve as supporting communication and earliest signal of intervention, adding value in extending the clinical decision-making process on chronic rheumatologic conditions.

Keywords: Disease Classification, Deep Learning, Personalized Recommendations. Rheumatoid Arthritis, Response Prediction.

Introduction

In 2024, a Master Protocol to Facilitate the Effective Translation of an Initial Chatbot Intervention (MARVIN) across various populations and health areas was designed (1). The adaptive platform consists of several concurrent individual chatbot sub-studies for a particular healthcare setting. Further, the influence of stakeholder and patient partnerships on chatbot development was determined by this model. In 2023, an algorithm to interact with and monitor RA patients remotely was developed (2). It gives data to the doctor in a handy format. Regular assessments of the life standards, functional limitations, and RA activity are conducted, and the suggestions are adjusted as needed. In 2024, AI-based technologies that could enhance patient care and decrease delayed diagnosis were created (3). In order to identify hand and peripheral nerve damage, Isabel and ChatGPT-4 were utilized. This study included cases from a virtual library. After receiving each list, two hand surgeons assessed the systems' performance separately. This model was useful in producing medical diagnoses; however, clinicians proceed with extreme caution and rely on their medical judgment during diagnosis. In 2023, a framework based on Arksey and O'Malley for the chatbot system was designed (4). This model highlights the information on patient involvement reported during the chatbot deployment process. It could serve as a roadmap for recording patient information and its integration into the chatbot development process. In 2024, ChatGPT-like solutions for treating RA with methotrexate were adopted (5). Clinical practitioners may benefit from these solutions for disease diagnosis, treatment, and clinical trials. ChatGPT-like solutions give patients quick access to vast volumes of information to provide safe and efficient care. In 2024, a cross-sectional study was carried out at a single center among 17 rheumato-

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-logy patients (6). Here, the comprehensiveness and readability of LLM chatbot answers are compared to physician-generated answers. Regarding accuracy, accessibility, and general choice, patients with rheumatology awarded AI-generated answers to their enquiries. Patients might not be aware of this discrepancy, which indicates that LLM chatbot responses are not as effective as physician responses. In 2021, the likelihood and timing of future RA were forecasted (7). Additionally, the obstacles to a paradigm shift in RA, where active risk assessment is aimed at enhancing the public health strategy for managing cardiovascular disease, were addressed. In 2023, a computer vision pipeline was used to quantify five features of the RA (8). These features were associated with the number of cells per unit of tissue in patients with both seronegative and seropositive RA. The level of expression of immunoglobulin heavy-chain genes in the synovial tissue was determined using this model.

RA is a chronic disease that causes disability, joint damage and destructive polyarthritis. Diagnosing this Rheumatoid arthritis is difficult on account of the overlapping symptoms of arthritis and early detection with management is needed for improving decision-making in clinical applications. The major challenges associated with the conventional Rheumatoid Arthritis management systems are provided in Table 1.

- Healthcare providers have no time to respond to patient queries and attaining clear information about patients is more challenging for healthcare professionals. In addition, analyzing the longitudinal patterns related to RA is a challenging issue in traditional AI-based models, and providing relationships between doctors and patients is a challenging factor in conventional approaches. In this work, a chatbot system is developed and it is used to maintain the relationship between the patient and doctors for managing RA.
- Traditional approaches do not provide self-management strategies including resource use, problem-solving, decision making and patient health related to RA. In this work, the intelligent model is developed for classifying the RA, which is used for providing recommendations to the user and it also helps to adopt the efficient decision-making process.
- There are no approaches available for providing clear, accurate and reassuring guidance for managing RA and hence new techniques are proposed here for providing instructions to the patients regarding side effects, treatment instructions, comorbidity management and drug interactions.
- The feasibility and usability of the RA management models are lower and it needs more samples for assessing the clinical effectiveness. Providing sustainability, fidelity, appropriateness, and cost-effectiveness for RA management is poor. So, this work proposed a deep learning-based chatbot system for effectively managing RA in humans.

RA is a symmetrical, and inflamed, systemic polyarthritis disease (9). As cartilage and bones erode, it usually results in joint damage. If left untreated, it results in a loss of muscle function, making it impossible to do everyday duties (10). Increased incidence of coronary heart disease and osteoporosis are among the additional health hazards associated with excessive inflammation (11). To avoid the development of arthritis and disability, early detection and therapy with Disease-Modifying Antirheumatic Medications (DMARDs) are essential (12). Some of the typical signs of RA, such as cartilage erosions, inflammatory nodules, and other extra-articular indicators, are typically absent in the initial stage of this disease (13). Multiple minor and major joints may be damaged by RA disease (14). The early observations usually happen with the help of the Metacarpophalangeal (MCP) joints of the hands. To diagnose RA and select the best Antirheumatic therapy to avoid joint degeneration, rheumatologists use a range of clinical indicators (15). Typically, standard radiographs are utilized to detect and track joint deterioration, which shows degradation and narrowing of the joint space (16). Reviewing the radiographs frequently requires a highly qualified medical practitioner. For assessing radiographs of RA, several grading techniques have been presented (17).

AI models are more reliable and effective for analyzing merely clinical data, and they can identify RA at much earlier stages (18). RA progresses quickly, and two of its most severe consequences are loss of ability and functional damage to joints (19). To avoid joint injury, loss of operation, and progression of the disease, early identification of RA is necessary (20). Additionally, it has been demonstrated that early treatment enhances patient outcomes, such as lower disease activity and enhanced quality of life. RA is difficult to diagnose early since some of its symptoms can be misinterpreted with the signs of other illnesses. The integration and analysis of enormous amounts of information from various sources to identify a pattern of RA can be demonstrated by the AI model. Most of these ailments affect patients' quality of life. Self-management of rheumatic disorders is greatly aided by rheumatologists' patient education. Patients are probably using Large Language Model (LLM) chatbots, particularly ChatGPT-4 and its variants for medical enquiries (21).

The use of ChatGPT-like solutions could be especially helpful when methotrexate is used to treat RA (22). In recent years, ChatGPT has closed the information gap and enhanced patient-provider relationships. For example, ChatGPT could assist in providing the risk-benefit analysis of various treatment alternatives, helping patients and healthcare providers. Along with presenting information on the disease, treatment options, possible risks, and anticipated results, it may also help people understand the technical aspects and complicated medical terms. This might allow patients to collaborate with medical experts in making well-informed decisions (23). ChatGPT provides two-way communication between medical professionals and patients to facilitate collaborative decision-making. When it comes to RA therapy, the usage of ChatGPT-like solutions in healthcare offers a great deal of possibilities to enhance patient-provider interaction (24). Even though there are other options, ChatGPT (OpenAI) has gained a lot of interest because of its advanced capabilities to improve rule-based chatbots. However, it is crucial to remember that ChatGPT-like solutions should be viewed as an integrated interface within a larger ecosystem that provides connectivity to many data sources rather than as a stand-alone solution. Using ChatGPT can facilitate more efficient and seamless interaction between the patient and the provider, which can enhance the standard of treatment (25, 26). So, this work promoted a chatbot system in the healthcare sector for curing RA in humans.

This research work made the following contributions that are listed in the below points.

- To suggest chatbot-based response prediction and RA classification with a recommendation system for creating the proper medical solution for the user with RA for tackling healthcare problems. Here, the chatbot system gathers information from the user at the same time it provides a proper response to the patient's query. Further, the early detection of RA and its associated treatments are adopted using this response, which provides proper clinical assistance for the patient affected by the RA. To manage RA, the proposed paradigm is used by the healthcare system for detecting high-risk patients and provides intervention for improving their lifestyle.
- To design ATG-LSMSA for query-based response prediction for determining the symptoms of RA in the patients. This ATG-LSMSA model acts as the communication model since it understands all users' queries and provides the reply with the appropriate solution. The input text of the user is initially matched with the previously included data that are collected from the patient through the questionnaire and this data is given to the ATG-LSMSA model, which acts as the knowledge base. The text input of the user is matched with the knowledge base via the ATG-LSMSA and responds according to the data.
- To design AND-TCN for RA classification and recommendation to patients to maintain a healthy lifestyle. This model uses the data from the symptoms and feed attained from the response prediction process. These symptoms and feed are analyzed by the AND-TCN for classifying the RA patients into high, low and medium categories. Based on the different classes of the RA, personalized recommendation is provided to the user to enhance better healthcare outcomes. In addition, the recommendation provided by the suggested model is used for optimizing the treatment strategies for enhancing the quality of life.
- To present RAV-WO from the WO for tuning the hidden neuron, activation function and learning rate in the ATG-LSMSA and AND-TCN for reducing the Word Error Rate (WER) and Sentence Error Rate (SER) in the query-based

response prediction and also it enhances the Critical Success Index (CSI) and precision in the RA classification and recommendation system. The RAV-WO has high searching capability so it can provide the most powerful solution to the complex optimization issues and it explores the entire search space with minimum computational load to attain excellent results in the RA classification and recommendation.

Table 1: Features and challenges of chatbot-based Rheumatoid Arthritis management system

Author (citation)	Methodology	Features	Challenges
Ma *et al.,* (1)	MARVIN	• It highly improves the relationship between patients and healthcare professionals. • It provides high-quality assessment related to Rheumatoid arthritis.	• It potentially introduces a bias towards the individuals.
Prokofeva *et al.,* (2)	Chat-bot	• It gives more attention to confidentiality, privacy and regulatory norms. • The effectiveness of the remote-control treatment is higher.	• It does not provide evidence-based solutions.
AlShenaiber *et al.,* (3)	ChatGPT-4	• It provides faster diagnostic accuracy. • The reliability of the model is higher.	• This method is required to explore the use of diagnostic clinical practice.
Sadasivan a *et al.,* (4)	Chatbot	• It provides sufficient patient engagement.	• More systematic reporting is needed for the implementation process.
Chen *et al.,* (5)	ChatGPT	• The accessibility, usability and fidelity of the model are higher.	• The time requirement is higher for providing solutions.
Ye *et al.,* (6)	LLM chatbot	• Better association between the patients and physicians is provided by this approach. • It decreases the message burden and alleviates the demand for physicians.	• It only generates responses related to patients' questions; evident solution is needed to improve healthcare system efficiency.
Deane *et al.,* (7)	Artificial intelligence	• It effectively provides the solutions for pre-rheumatoid arthritis management.	• Prediction methods are not effectively described in this method.
Frezza *et al.,* (8)	Computer vision Algorithms	• High-resolution quantification is generated using this model.	• Analysis steps are not effectively provided by this approach.

Methodology

Architecture Representation of Implemented Chatbot-Based Rheumatoid Arthritis Management

System Need for Rheumatoid Arthritis Management System Based on Response Prediction

The destructive polyarthritis, disability and joint damage occur because of the chronic disease called

RA. Presently, laboratory and clinical features are used for the detection of RA. The symptoms of RA overlap with other arthritis, which renders RA detection as a complex task. Better management of RA is attained by the early detection of RA in the human. To evaluate the effects and improve the medical diagnosis of RA, the query-based response prediction system is incorporated with the RA detection model. With the help of the response prediction system, the user can attain the proper medical solution to prevent the severe effects of RA. The complex nature of the RA and variability in the patient response to the treatment are the major reasons for the development of the RA management system. The quality of life of the patient is greatly affected by RA since it causes inflammation, joint damage and pain in the human. The traditional management process is not sufficient because of the multifaceted nature of the RA. The treatment history of the patients, response to the previous therapies and patient's clinical data are analyzed by the predictive management system with the help of a deep learning model. The response from the patients for the specific treatment options is adopted by this model to provide tailored treatment to the RA. The response predicted by the patients can be used for adjusting the treatment to enhance the quality of care of the people affected with RA.

Proposed Model and Description

In this research, a chatbot-based RA management system is developed with the help of deep learning to treat RA in human at an earlier stage to enhance their lifestyle. Further, the massive problem associated with RA is prevented by the chatbot system, which contributes to enabling the connection between the computers and the user in a natural manner. The chatbot is one of the modern forms of interaction. The chatbot system solves problems like humans and it quickly responds to the user's query, the other name of the chatbot is the answering engine or communicational agent. In this research, the new deep learning model named as ATG-LSMSA is used for training the chatbot system that can be used for maintaining the interaction with the user through text-based messages. The query of the user is easily understood by the ATG-LSMSA and it also makes efficient and smooth communication with the user. The data in the form of input query is given into this system so the working of this application is very simple as compared to the other models. The context of the input over the longer sequence of the input data is learned by the ATG-LSMSA model. Further, the relevant information from the query or its interactions is preserved by the LSTM since it manages the memory of the model. Further, the importance of the different words is weighted by the self-attention included in this model also it concentrates on a significant portion of the data to get accurate results in the response prediction process. Further, the information given to the model is analyzed at various levels through the SMSA. The personalized questions related to the health condition, lifestyle choices and symptoms are asked by the ATG-LSMSA-based chatbot system. The ATG-LSMSA-based response prediction system (chatbot) can assist the user in attaining the symptoms of the disease. The personal details of the user are given to the ATG-LSMSA chatbot model. The symptoms from the user are then asked by the chatbot system via NLP. Once, the user asks the question to the chatbot system then it asks a series of questionnaires to collect the relevant healthcare information. From the responses of the user, the proposed ATG-LSMSA determines the correlation and pattern between the feedings and symptoms to form the data. The parameters including hidden neuron, activation function and the learning rate are tuned using RAV-WO for reducing the WER and SER in the response prediction process. These data are then passed to the AND-TCN for the detection and classification of the RA. The relevant features from the temporal data are extracted by the AND-TCN model for the effective diagnosis of RA. Further, RA patients are effectively classified by the AND-TCN because of the dilated convolution that helps to recognize the complex patterns in the data. The efficiency of the RA classifications and its associated computational cost are reduced through the dilated convolution layer. The computational load and parameter requirement of the AND-TCN is reduced with the help of the nested connection within this model. Here also, the hidden neuron, activation function and learning rate are tuned using the RAV-WO for improving the CSI and precision in the RA classification. The AND-TCN classify the RA into low (0 to 40), medium (40 to 70), and high (70 to 100), based on the predicted score values. Finally, the recommendations in the form the dietary advice and physical activity are provided to the user based on the classified RA. A brief comparison of the proposed model concerning the conventional approaches is taken to prove the effectiveness of the developed RA management system. The structural illustration of the proposed model is given in the Figure 1.

There are several reasons why AND-TCN is chosen as opposed to recurrent or purely attention-based models. First, AND-TCN efficiently models long-range temporal dependencies with parallel processing over history, thus overcoming the vanishing gradient problem in RNN and LSTM. Second, the dilated and nesting structure increases the receptive field without enhancing model depth more, facilitating effective processing of sequential RA symptom patterns. Third, AND-TCN has lower time complexity and converges faster to the optimal solution as compared with others like multi-modal fusion or transformer-only frameworks while keeping clinical interpretability. These characteristics render it applicable to real-time patient monitoring and for clinical use.

Description of Rheumatoid Arthritis Data

The required knowledge data is collected from the RA-affected patient via several questionnaires. Here, the symptoms of the RA-affected patient and their experience after receiving the treatment are gathered by asking questions to the user. The relevance and the severity of the RA symptoms are understood via the generated questionnaires. The collected data from these sources is denoted by the term H_n and here $n = 1,2....N$ the total number of data is represented by the term N.

The system mainly relies on symptom descriptions and responses to questionnaires as input modes. These variables are also pre-processed to obtain organized sequences of temporal features, which represent them in the same way. The AND-TCN takes advantage of dilated convolution layers to learn short- and long-term dependencies over these heterogeneous inputs, guaranteeing that the variability in symptom patterns can be well-modeled.

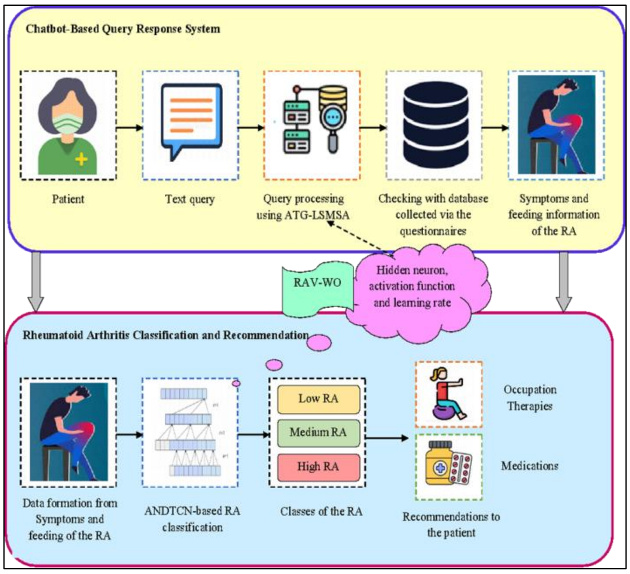


Figure 1: Structural Illustration of the Proposed Model

Generative Artificial Intelligence-Based Query Generation and Response Prediction System for Rheumatoid Arthritis Management

Trans-Generative LSTM with Sparse Multiscale self-attention

The response prediction for the management of the RN is done using the Trans-Generative LSTM with a Sparse Multiscale Self-Attention model. This model is made up of several components such as a transformer, Generative LSTM and Sparse Multiscale Self Attention that continuously ask questions on the patients to provide required responses related to the symptoms of RA. The sequential modelling issues are effectively solved with the help of the Transformer (27). This module is well suited for handling the long-term input sequence. The sequence of tokens $(y_1,....y_m)$ is initially taken by the encoder of the transformer model, which provides the memories in the form of latent representation denoted as $a = (a_1,\dots a_m)$, the one-by-one conditioning on a is applied to get the output sequence from the decoder represented as $(u_1,\dots u_o)$. The Multihead attention in the transformer performs the attention in a parallel manner and it projects the keys, values and queries. The expression of the multi-head attention is denoted in the Eq. [1].

$$P_j = attention(R_j, L_j, W_j) = sftmx\left(\frac{R_j L^T{}_j}{\sqrt{e_l}}\right) W_j \quad [1]$$

Here, the query matrices are represented as $R_j = RX_j^R$, key matrices $L_j = LX_j^L$ and the term $W_j = WX_j^W\ (j = 1,\dots i)$. The identical layers are stacked in the encoder of the transformer, the Multihead attention component and feed-forward network are the two sub-layers of the network. The same components of the encoder are repeated in the decoder network here the multi-head attention on the output is performed by adding an extra sublayer. The different parts of the input sequence are focused by the Multihead attention.

The sequence of data is generated by the generative LSTM (28). The long-range dependencies of the sequential data are effectively captured by the LSTM since it prevents the vanishing gradient issues while retaining the information over a longer period. The patterns and structures within the data are learned by the generative LSTM model by performing the training process. Here, the LSTM model is more appropriate for the sequential data. In the LSTM model, the information flow is regulated via the cell and gates and it is used for circumventing the short-term memory loss within the network. The gates in the LSTM model play the most important role in maintaining or regretting the information that has been kept within the network. Throughout the processing stage, the relevant information about the data is carried out by the cells of the LSTM. The output P_b, forget gate G_b and input gate J_b are used for controlling the cells of the LSTM model. Here, the prior, present and temporary cell states are denoted as L_{b-1}, L_b and $\hat{L}_b$. Within the gates, the activation functions the form of $\tan h$ is used for maintaining the values between zero to one. The information is forgotten if the values are closer to zero and the information is kept sustained if the value is close to one. The information discarded from the prior cell or incorporated with the present cell is decided by the gates J_b, P_b and G_b, respectively they are expressed as follows:

$$G_b = \varpi\left(X_g \cdot [I_{b-1}, y_b] + C_g\right) \quad [2]$$

$$J_b = \varpi\left(X_j \cdot [I_{b-1}, y_b] + C_j\right) \quad [3]$$

$$P_b = \varpi\left(X_p \cdot [I_{b-1}, y_b] + C_p\right) \quad [4]$$

Here, the weight matrices are represented as X and the offset vectors are denoted as C.

$$I_b = P_b * \tan h(L_b) \quad [5]$$

The hidden state is calculated using the above Eq. [5].

$$\varpi = \frac{1}{1+e^{-y}} \quad [6]$$

$$\tanh = \frac{e^y - e^{-y}}{e^y + e^{-y}} \quad [7]$$

$$MHA(R, L, W) = concat(B_1,\dots B_i) X^P \quad [8]$$

The efficiency and the scalability of the traditional self-attention are solved using the SMSA (29) and it has the capability to handle the dependencies of the data at multiple scales. The quadratic challenge of conventional self-attention is solved using the SMSA. The longer time scale correlation, which is weak and diurnal and is captured by the temporally multiscale nature of the SMSA (30). In the SMSA, a total O number of attention heads is adopted. The attention to the different aspects of the information is provided by the SMSA and here the head index is represented as $j = \{1,2,3....I\}$. Here, the attention matrix $M \times M$ is sparsified by the sparse attention mask. In the SMSA, the attention score at every head is determined through the scaled dot attention. The linear projection is done with concatenated output, which is done by taking the output from each attention head and it is given in Eq. [8].

In Eq 8, the term $X^P = v^{e_{network} \times e_{network}}$ and the attention score are expressed as B . The pictorial illustration of the Trans-generative LSTM with sparse multiscale self-attention is given in Figure 2.

Query-based Response Prediction using ATG LSMSA

In order to provide quick therapies to the RA and also prevent the massive problem in the RA, the chatbot system also called as query response prediction system is proposed using the ATG-LSMSA, which facilitates maintaining the interconnection between the computer and user naturally. The Query-based Response Prediction using ATG-LSMSA acts like a human and provides a quick response to the query of the user. In this research, the ATG-LSMSA is used for training the chatbot system where it makes communication with the user through text messages. The ATG-LSMSA can facilitate efficient interaction with the user query and respond with the appropriate solution. Here, the ATG-LSMSA model matches the query of the user in the form of text with the previously incorporated data thus responding to the query asked by the user according to the data. Here, the data or the knowledge is taken from various surveys and individualized queries. Without any delay, the ATG-LSMSA-based response prediction system responds to the query in 24×7 . In the digital world, the proposed ATG-LSMSA acts as a communicational agent and it helps to promote healthcare-related actions on a large scale. In this work, the chatbot system is made with the help of ATG-LSMSA since it analyses the user's question and predicts the correct reply and response to the query. During the training of the chatbot model, the sequential data is provided to the ATG-LSMSA. All different kinds of queries are given as the input and are segregated by the ATG-LSMSA for providing the correct output (response to the user). What types of queries have been answered should be in the training process so it is considered as the main part of this process.

The ATG-LSMSA is utilized by the chatbot system. Based on the query of the user, the correct answer will be predicted by the chatbot. Here, the user just writes the text message on the interface of the chatbot and it utilizes the ATG-LSMSA model to make the prediction. The queries given by the user are initially tokenized to attain the individual phrases and words. Further, the embedding process is carried out on the tokenized query for embedding into vector space. Further, the ATG-LSMSA processes the embedded query where the importance of the different words or phrases in the query is focused by the attention module.

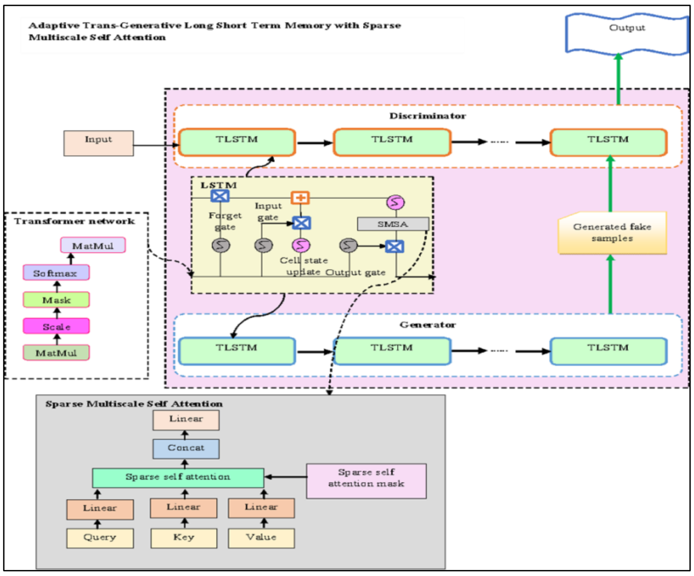


Figure 2: Trans-generative LSTM with Sparse Multiscale Self-Attention

Subsequently, specific parts of the query are selectively focused by the SMSA and the results from these components consist of nuances regarding the patient's queries. From the knowledge graph or the database, the relevant knowledge is retrieved using the contextualized representation of the query.
Finally, the response to the patient's query is generated by the retrieved knowledge. If the user does not want to continue, then they can click the exit button or else they can continue the interaction. Here, the parameters such as a hidden neuron, activation function and the learning rate are tuned using RAV-WO for reducing the WER and SER on the query-based response prediction. The consideration of the above hyper parameters improves the training efficiency of the model so it provides better results in the query-based response prediction task. The objective function of the RAV-WO-ATG-LSMSA-assisted query-based response prediction is given in Eq. [9].

$$F1 = \underset{\left\{o_p^{rav-atg},\, q_u^{rav-atg},\, w_u^{rav-atg}\right\}}{\arg\min} \left(SER + WER\right) \qquad [9]$$

Here, the objective function is represented as $F1$, the optimized hidden neurons is $o_p^{rav-atg}$ in $[5,255]$, the optimized learning rate is represented $q_u^{rav-atg}$ in $[0.01,0.99]$ and the optimized activation function is represented as $w_u^{rav-atg}$ in $[1,5]$.

$$SER = \frac{F}{U} \qquad [10]$$

$$WER = \frac{T + E + J}{O} \qquad [11]$$

Here, the sentence with the least error is represented as F, and the total number of sentences is denoted as U. The total count of the substitution is represented as T, the missed word is E, the incorrectly added words are denoted as J, and the total number of words in the sentence is denoted as O. The pictorial illustration of the RAV-WO-ATG-LSMSA-assisted query-based response prediction is given in Figure 3.

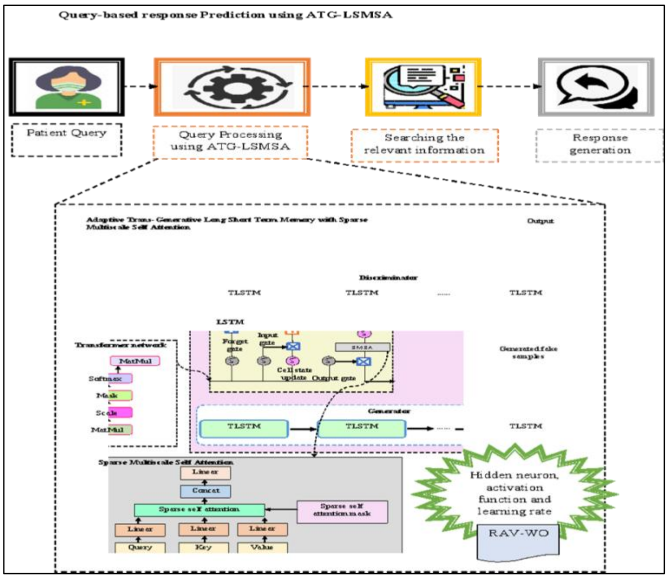


Figure 3: V-WO-ATG-LSMSA-Query-Based Response Prediction

Proposed RAV-WO

An efficient optimizer named as RAV-WO is proposed for tuning the parameters of the models used for the query-based response prediction and RA classification process. The RAV-WO's candidate solution thoroughly looks at the problems to provide a better solution. The learnable parameter of the model used in both RA classification and the chatbot-based response prediction is iteratively adjusted by the RAV-WO to minimize the loss of accuracy in the response prediction and RA classification. Here, the random number is improved for thoroughly exploring the search space. Further, the RAV-WO derived from the conventional WO maintains the proper balance between the exploration and the exploitation to prevent the probability of sticking in the local optima. The RAV-WO is more effective for resolving the global optimization issues with the suggested mechanism. It prominently exploits the search process for enhancing the convergence rate while eliminating the local optimal solution. The natural activity of the wombat in the foraging process in the wild is followed by the WO (26). The WO is well suited for solving the design engineering issues. The balanced equilibrium between the exploitation and exploration of the WO can be used for solving Mult-objective optimization problems. However, the large and the multi-dimensional space are not explored by the WO and it only provides suboptimal results in the high-dimensional search space. It also encounters some issues such as high computational demand and premature convergence in the search operation. The uncertainties encountered in the conventional WO are solved by modifying the random number in the WO. The RAV-WO provides solutions to complex optimization problems and it has the capability to explore the search space in a more efficient way. The excessive computational requirement of the WO is prevented by the newly determined random number and it is mathematically expressed in Eq. [12].

$$G = \frac{po^2}{wo^2 + po^2/25} \qquad [12]$$

Here, the improved random number is denoted as G, the worst fitness is wo, and the current fitness is po. The RAV-WO tunes the hidden neuron, activation function and learning rate for enhancing the CSI and precision in RA classification. In addition, the WER and SER in the query-based response prediction are reduced by the RAV-WO-based parameter optimization. The RAV-WO provides the optimal results in high dimensional search space and it also prevents the computational demand as well as premature convergence rate in the searching process. The pseudocode of the RAV-WO is given in the Algorithm 1.

Algorithm 1: RAV-WO

Input: Hidden Neurons Of ATG-LSMSA and NDTCNA, Learning Rate Of ATG-LSMSA and NDTCNA, Activation Function Of ATG-LSMSA and NDTCNA

Output: Optimized Hidden Neurons of ATG-LSMSA and NDTCNA $o_p^{rav-atg}, o_l^{rav-andtcn}$, Optimized Learning Rate Of ATG-LSMSA and NDTCNA $q_u^{rav-atg}, q_k^{rav-andtcn}$ And Optimized Activation Function Of ATG-LSMSA and NDTCNA $w_u^{rav-atg}, w_l^{rav-andtcn}$

While the termination is not fulfilled
Fix the population size O and iteration U
    For $u = 1\ to\ U$
        For $u = 1\ to\ U$
            Phase 1: Exploration phase
            Improve the random number using Eq. [13].
            Find the foraging position of the wombat and select the target foraging of the wombat to update the position.
            Phase 2: Exploitation phase
            Find the new position of the wombat and upgrade the position.
        End for
    Save the best solution
    End for
End while
Stop

Rheumatoid Arthritis Management and Recommendation System Using Advanced Deep Learning Model

Data Formation from Symptoms and Feedings

The symptoms and feedings of the disease are attained from the chatbot-based response prediction system. Here, the records of the user are stored using the database of the system. The information from the chatbot is responsibly processed and it has been transformed into data. The response from the chatbot will be passed to the backend. Without referring to the backend, some logical reasoning and responses are performed by the chatbot. The data of the user formed from this process is stored and segregated. In this way, the responses are recorded in the form of the data on the chatbot system. The data formed from the symptoms and feedings are further utilized by the AND-TCN model for the RA classification and recommendation.

Developed AND-TCN

The temporal dependencies in the sequential data are captured by the nested dilated convolution layers of the AND-TCN and it does not enhance the parameters available in the network. The patterns of the data are deeply analyzed by the long-term dependencies of the model. It can effectively learn complex patterns through the dilated convolution and nested structure of the AND-TCN. The dilated convolution and casual convolution available in the AND-TCN enhance the parallel computing capabilities and modeling capability of the network. The convolution layers of the AND-TCN gather the long-term dependencies in the data and it also improves the inference speed in the detection of RA. When processing the high dimensional non-linear data, because of the higher feature extraction capability. The input data is represented by the term $Y = \{y_1, y_2, ... y_U\}$ here the characteristics of the data at the time u are represented as y_U. The casual convolution is the core of the TCN (31) and here the time series data is modeled by the 1D convolution. The historical data $z_1, z_2, ... z_U$ .is depends on the casual convolution at the time step U. The calculation for the 1D convolution kernel x is represented in the Eq. [13].

$$i_u = \sum_{j=0}^{l-1} x_j y_{u-j} \qquad [13]$$

Here, the size of the convolutional kernel is represented as l, the dilated factor e with the dilated convolution is used by the TCN for enhancing the receptive field.

$$i_u = \sum_{j=0}^{l-1} x_j y_{u-ej} \qquad [14]$$

Only fewer layers are used for capturing the long-term dependencies in the data. Finally, the classification of the RA is done by using the fully connected layer and it is expressed in Eq. [15].

$$z_u = \aleph(Xi_u + c) \qquad [15]$$

The SoftMax normalization is represented as $\aleph(.)$, and the trainable parameters are represented as c. The pictorial illustration of the AND-TCN is given in the Figure 4.

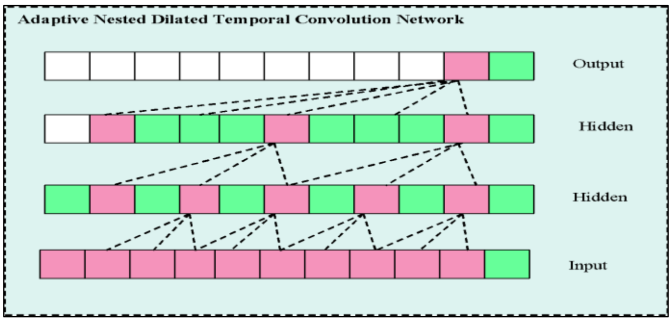


Figure 4: Pictorial Illustration of the AND-TCN

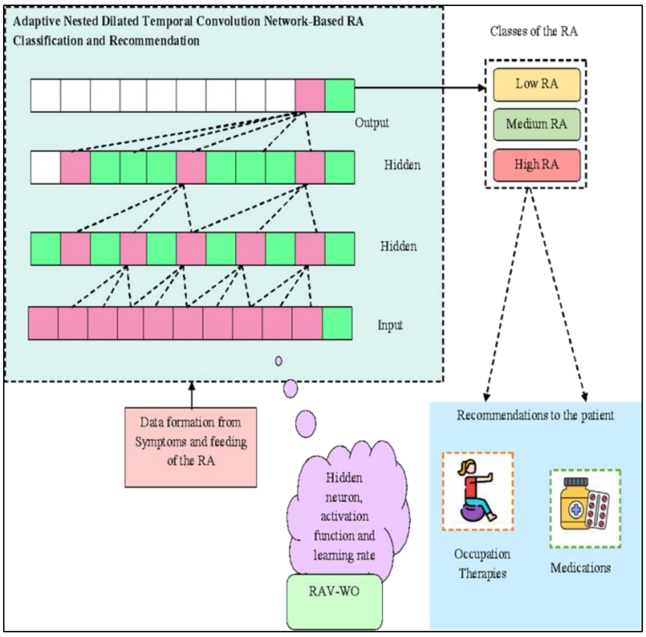


Figure 5: Pictorial Illustration of the AND-TCN-Based RA Detection and Recommendation

Chatbot-based Rheumatoid Arthritis Classification and Recommendation using AND-TCN

The data generated from Symptoms and Feeding of the response prediction process is utilized by the AND-TCN for the RA classification. The AND-TCN model analyses the generated data to perform the RA classification and the recommendation. Here, the nested structure consists of more connections that enhance the receptive field to get better results. The complex pattern of the patient data is captured by the nested dilated structure of the AND-TCN so the accuracy of the RA classification is greatly improved. Further, the multiple features of the data are extracted by the dilated convolution layer of the model. Also, it has the capability to extract the long as well as short-term dependencies of the RA. The noise effect in the data is greatly reduced by the nested and dilated connections of the AND-TCN that facilitate to attainment robust results in the RA classification. The features and patterns that contribute to the RA are provided by the AND-TCN model so it provides accurate and better results in the RA detection as well as classification. Further, the early detection of RA is improved by the AND-TCN's feature learning and multiscale feature extraction capability. The data formed from the symptoms and feedings of the response prediction are given to the AND-TCN model. Further, the depth of the network is exponentially increased by the dilation rates used by the nested dilated convolution, which helps to retrieve the features from the data at multiple scales. Then, the convolution filters in the AND-TCN model slide over the data to capture the temporal dependencies. Then the important information in the features is retained by reducing the temporal and spatial dimension through the pooling layer that is responsible for the task of the down sampling. Further, the feature maps are converted into vector format through the flattened layer. After, the complex patterns are recognized by transforming the feature vector into high-dimensional space. Finally, based on the score of the RA, the disease is classified into high, low and medium. Based on the classified RA, recommendations are given to the patient for enhancing their lifestyle. If the patient has low RA, then medications are suggested to maintain the disease activity and also used for managing the stress level and the patient with medium RA adopts occupational therapies for managing the lifestyle. Likewise, the patient with high RA can adopt aggressive medical treatment and hospitalization for treating the RA. Further, The RAV-WO tunes the hidden neuron, activation function and learning rate for enhancing the CSI and precision in RA classification. The objective function of the AND-TCN-based RA classification is given in Eq. [16].

$$F1 = \underset{\left\{o_l^{rav-andtcn}, q_k^{rav-andtcn}, w_l^{rav-andtcn}\right\}}{\arg\min} \left(\frac{1}{CSI} + \frac{1}{Pecs} \right) \quad [16]$$

Here, the objective function is represented as $F1$, the optimized hidden neurons of AND-TCNA $o_l^{rav-andtcn}$ in $[5,255]$, the optimized learning rate of NDTCNA is $q_k^{rav-andtcn}$ in $[0.01,0.99]$, and the optimized activation function NDTCNA $w_l^{rav-andtcn}$ in $[1,5]$. The CSI and precision are determined as follows:

$$CSI = \frac{t}{t+f+ff} \quad [17]$$

$$Pecs = \frac{t}{t+f} \quad [18]$$

Here, the true positive is t, false positive is f and false negative is ff. Figure 5 depicts the Pictorial illustration of the AND-TCN-based RA detection and recommendation.

Results and Discussion

Simulation Environment

The suggested paradigm was perfectly operated in the Python software. The experimentation was comfortably done with the presence of iteration, chromosome length and population and they are adopted as 50, 3 and 10. For discussing the performance of the developed model, the prior models such as Three Optimizers (TOT) (32), Sparrow Search Algorithm (SSA) (33) and Sculptor Optimization (SO) (34), AI (7), TCN (31), CNN (35) and LSTM (28) were adopted.

To evaluate the models, stratified k-fold cross-validation (k = 5) was performed, enforcing a balanced class distribution among folds. Stratification ensured the proportion of low, medium, and high RA severity categories was maintained in training and validation. External test sets were not present for this work, but their inclusion in future research will be instrumental to finally determine generalizability.

Evaluation Metrics

To test the proposed model, Accuracy, F1-score, FNR, FPR, and Sensitivity are utilized.

$$accuracy = \frac{t+tt}{t+tt+f+ff} \quad [19]$$

$$f1score = \frac{2t}{2t+f+ff} \quad [20]$$

$$fnr = \frac{ff}{t+ff} \quad [21]$$

$$fpr = \frac{f}{f+tt} \quad [22]$$

$$sensitivity = \frac{t}{t+ff} \quad [23]$$

Sample from Chatbot System

Figure 6 shows the sample chatbot response from the proposed model.

Comprehensive analysis of the proposed response prediction system

To test the performance of the response prediction system, the experimental scenario of the proposed ATG-LSMSA with the existing model is displayed in Figure 7. It can be agreed from Figure 7 that the suggested ATG-LSMSA reaches accuracy from 90.6 to 94.9 when varying the K fold from 1 to 6. The constant rise in the accuracy of the proposed ATG-LSMSA showcases its performance in the query-based response prediction system. The 2nd highest value of accuracy is attained by the SO-ATG-LSMSA (90.2%) in the 3rd k-fold value. As it can be noted from the results, the WER of the proposed ATG-LSMSA is very low at the 3rd K fold value and the same case is maintained before and after the 3rd fold value. The results reported in Figure 7 showed that the proposed ATG-LSMSA response prediction system becomes more and higher accurate than the conventional models. The suggested ATG-LSMSA does not cause issues in the response prediction system since it provides higher accuracy and sensitivity values.

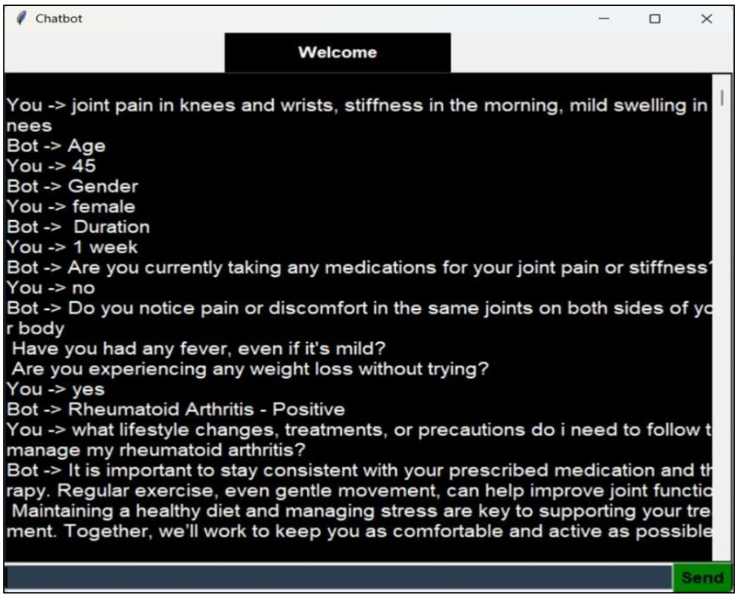
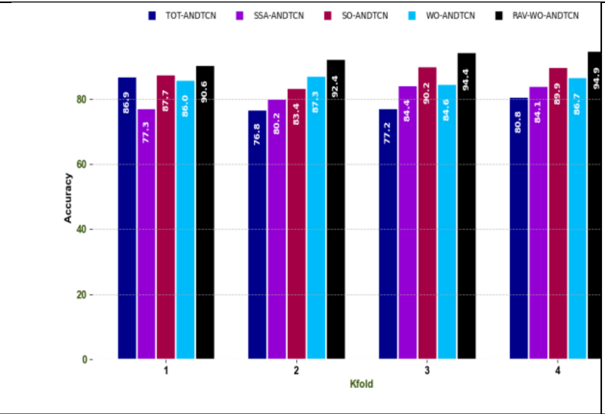
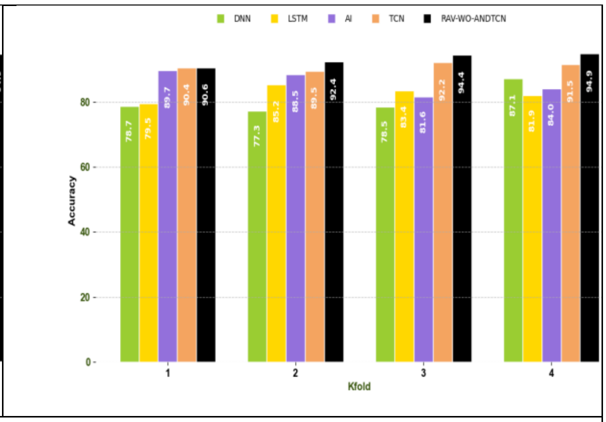


Figure 6: Sample Query-Response from Chatbot

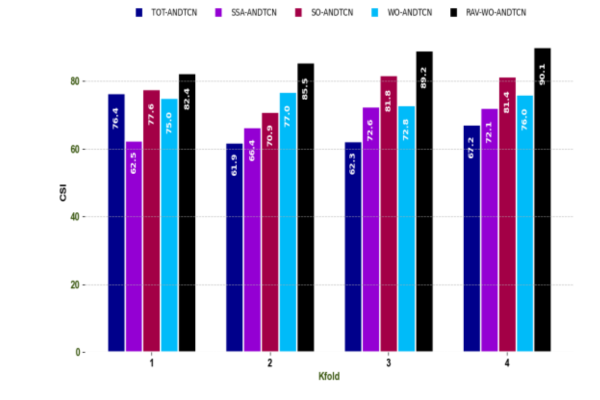
When the user asks some queries to the chatbot system, the proposed ATG-LSMSA model makes good conversation with the user and provides the perfect reply. Further, the results outlined in Fig.6 confirm the robust and inter-user communication between the users. In addition, the proposed ATG-LSMSA provides an understandable, quicker and more accurate response in the context of conversation. This model provides a user-friendly interface for providing accurate responses to the query of the user. From a prospective point of view, the presented model can be introduced in daily practice as an aid to decision-making during rheumatology consultations. Chatbot receives the symptom details from the patients, and AND-TCN labels these symptoms in levels of severity. Recommendations for lifestyle, therapy, and medication are derived; the last two are directly based on presently valid clinical guidelines. These results may allow rheumatologists to consider high-risk patients, remotely follow disease progression, and minimize consultation delay. This integration not only promotes self-management from patients but also deals with resource limitations in the clinic.

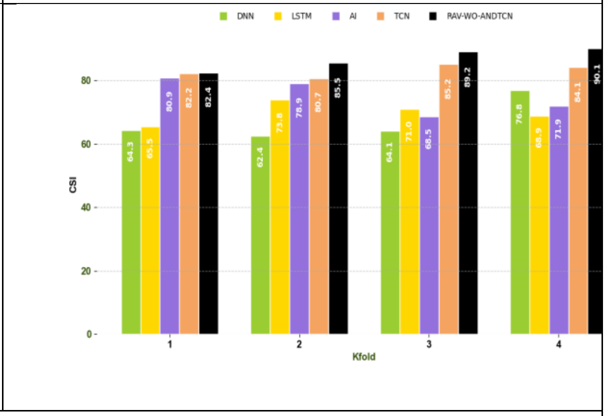
The recommendation engine combines data-driven predictions with clinical relevance. Although the prediction results are based on patient-reported symptoms only, the recommendation layer maps the prediction to evidence-based management guidelines of RA. For example, low severity classes are assigned to lifestyle modification advice whereas high severity classes are recommended to physician-mediated therapies. In so doing, this hybrid approach maintains clinically relevant recommendations but remains anchored in personalized, data-driven insights.


TOT-ANDTCN
SSA-ANDTCN
SO-ANDTCN
WO-ANDTCN
RAV-WO-ANDTCN
Accuracy
Kfold
86.9 77.3 87.7 86.0 90.6
76.8 80.2 83.4 87.3 92.4
77.2 84.4 90.2 84.6 94.4
80.8 84.1 89.9 86.7 94.9


DNN
LSTM
AI
TCN
RAV-WO-ANDTCN
Accuracy
Kfold
78.7 79.5 89.7 90.4 90.6
77.3 85.2 88.5 89.5 92.4
78.5 83.4 81.6 92.2 94.4
87.1 81.9 84.0 91.5 94.9

(A)


TOT-ANDTCN
SSA-ANDTCN
SO-ANDTCN
WO-ANDTCN
RAV-WO-ANDTCN
CSI
Kfold
76.4 62.5 77.6 75.0 82.4
61.9 66.4 70.9 77.0 85.5
62.3 72.6 81.8 72.8 89.2
67.2 72.1 81.4 76.0 90.1


DNN
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TCN
RAV-WO-ANDTCN
CSI
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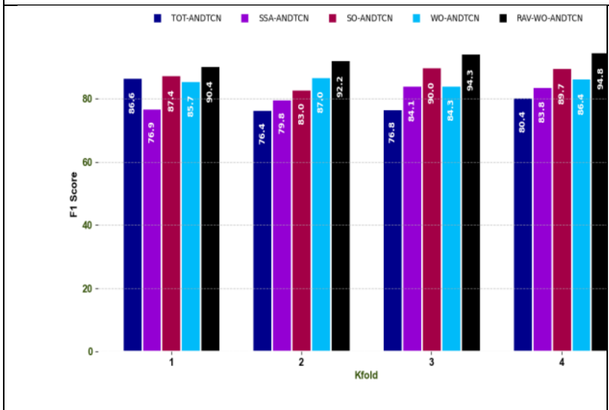
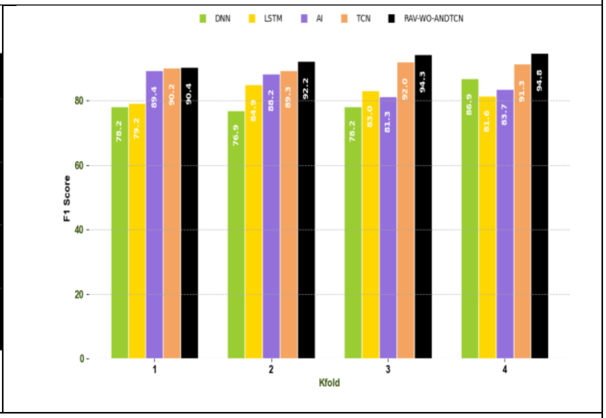
64.3 65.5 80.9 82.2 82.4
62.4 73.8 78.9 80.7 85.5
64.1 71.0 68.5 85.2 89.2
76.8 68.9 71.9 84.1 90.1

(B)


TOT-ANDTCN
SSA-ANDTCN
SO-ANDTCN
WO-ANDTCN
RAV-WO-ANDTCN
F1 Score
Kfold
86.6 76.9 87.4 85.7 90.4
76.4 79.8 83.0 87.0 92.2
76.8 84.1 90.0 84.3 94.3
80.4 83.8 89.7 86.4 94.8


DNN
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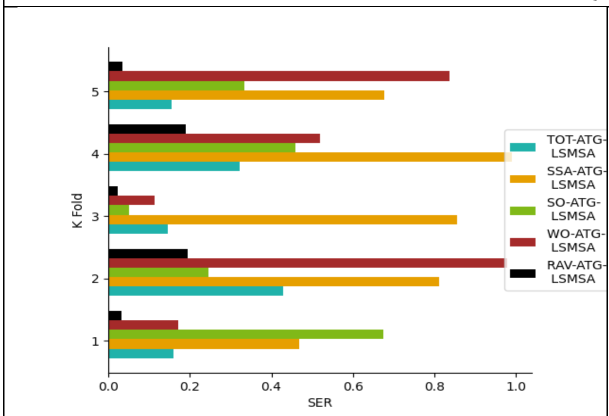
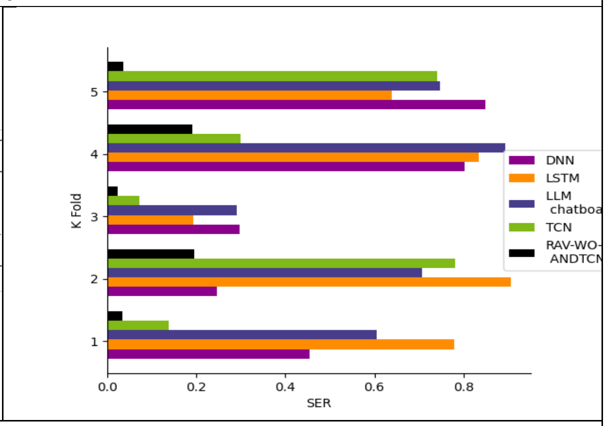
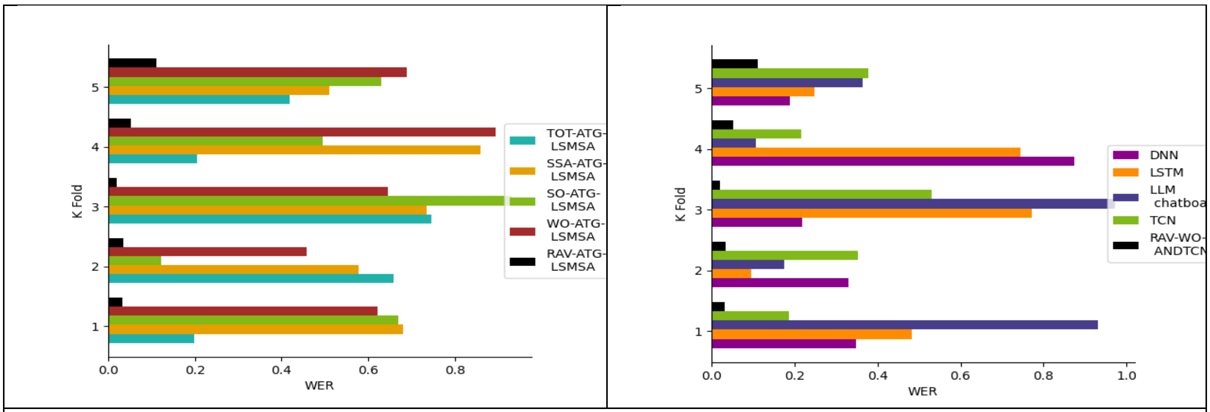
AI
TCN
RAV-WO-ANDTCN
F1 Score
Kfold
78.2 79.2 89.4 90.2 90.4
76.9 84.9 88.2 89.3 92.2
78.2 83.0 81.3 92.0 94.3
86.9 81.6 83.7 91.3 94.8

(C)


TOT-ATG-LSMSA
SSA-ATG-LSMSA
SO-ATG-LSMSA
WO-ATG-LSMSA
RAV-ATG-LSMSA
K Fold
SER


DNN
LSTM
LLM chatboa
TCN
RAV-WO-ANDTCN
K Fold
SER

(D)

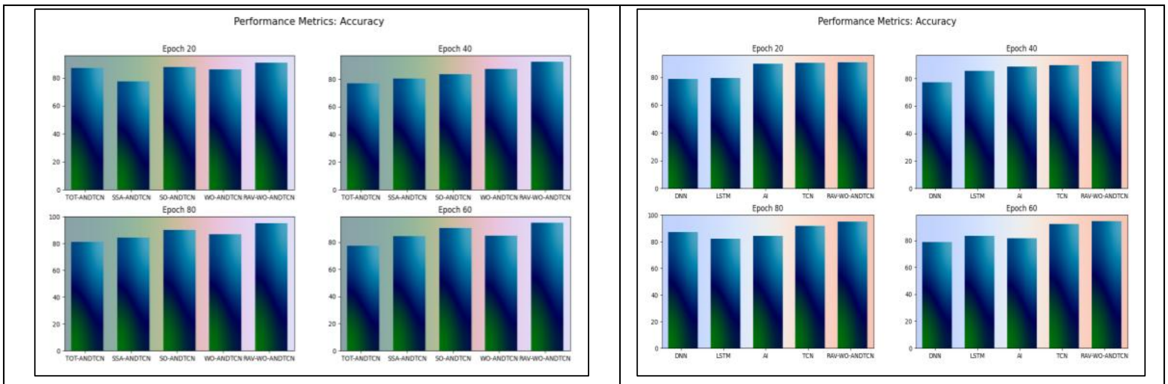


(E)

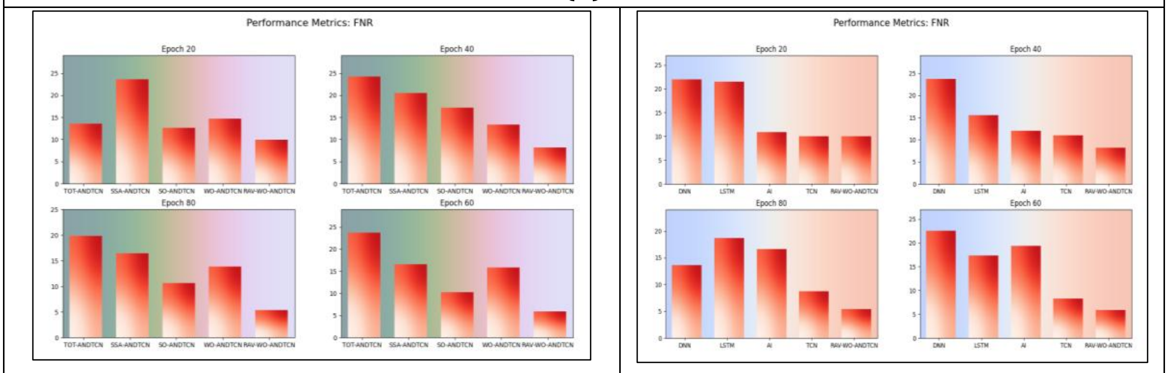
Figure 7: Performance Validation of the Response Prediction Model in terms of **(A)** Accuracy, **(B)** CSI, **(C)** F1score, **(D)** SER, **(E)** WER

Testing Results of the Proposed RA Classification Model

The results of the AND-TCN in the RA classification can be found in Figure 8. Because of the combination of the nested connection with the DTCN model, the proposed AND-TCN contributes to providing the most accurate performance in the RA classification with an accuracy of 92%. It can be found in all graphs that with an increase in performance when the epoch is varied from 0 to 100. With the proposed AND-TCN, the sensitivity value of 91% is attained in the RA classification task. Thus, it is revealed from Figure 8 that the suggested AND-TCN provides the best results from the clinical perspective where it can provide reasonable results in differentiating different classes of RA. The AND-TCN model considers the inflammatory signs attained from the response prediction system to get improved RA detection. The suggested AND-TCN-based RA classification can be used for improving patient outcomes since it detects and classifies RA at an earlier stage to prevent joint deformation and erosion in humans. Further, the suggested AND-TCN avoid the risk factors associated with RA and prevents the chance of disability in humans.



(A)



(B)

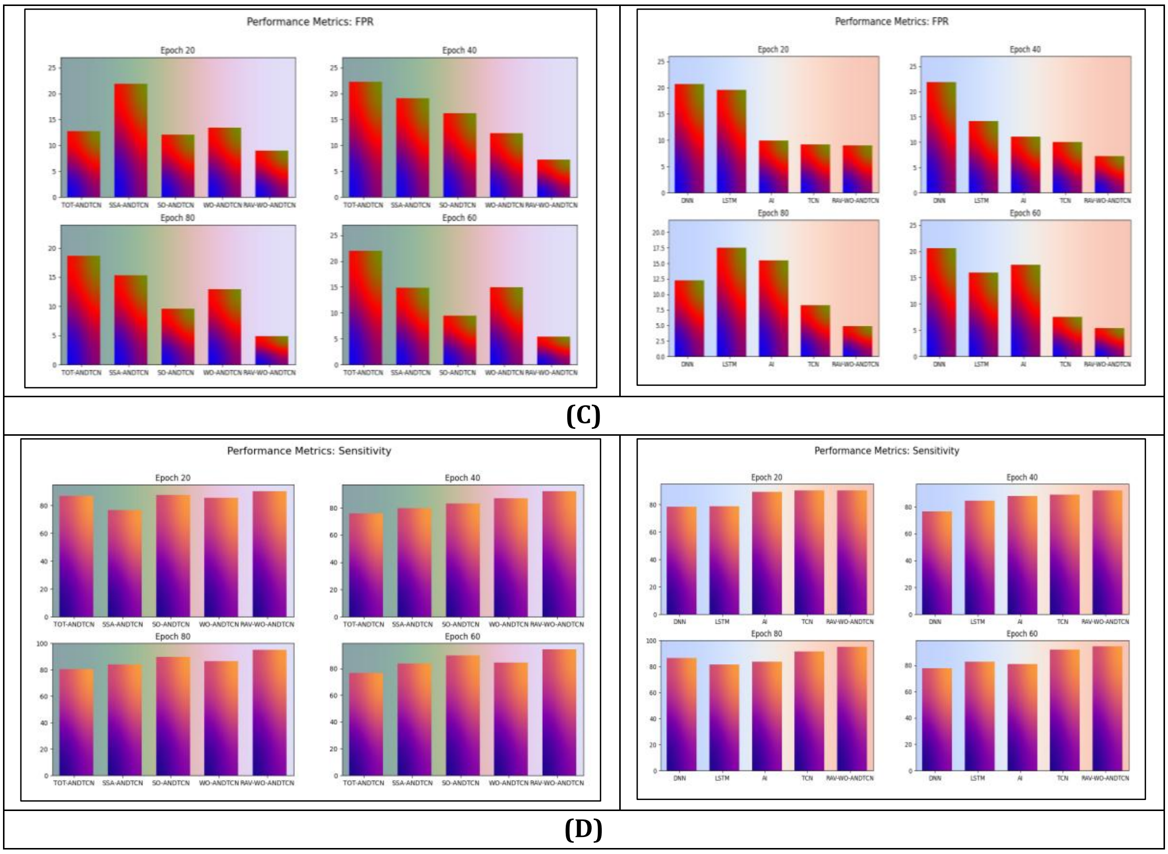


Figure 8: Performance Validation of the RA Classification Model in terms of **(A)** Accuracy, **(B)** FNR, **(C)** FPR, **(D)** Sensitivity

Results from the Recommendation System

Figure 9 shows the recommended performance of the proposed AND-TCN in the RA disease. At the learning percentage 75, the proposed AND-TCN model attained a hit rate beyond 95% which is higher than the AI, TCN, CNN, and LSTM. So, the recommendation results of the proposed model showed that the AND-TCN model provides recommendations to the patient based on the RA score for enhancing the quality of life.

Convergence Analysis

The remarkable problem-solving capability of the RAV-WO towards the optimization problem is determined by performing the convergence analysis given in Figure 9. As noted from Figure 10, the convergence of the proposed RAV-WO has stable results from the starting to the final stage of the iteration without stagnant on the local optimal condition which is confirmed by the straight line of the proposed RAV-WO throughout the convergence graph. Here, some modifications are made in the conventional WO to avoid premature convergence results. Further, the RAV-WO effectively locates the optimal solution for global and local optimization problems. Further, the RAV-WO relatively provides the optimal solution in terms of multiobjective optimization problems. The new variant of the RAV-WO solves the poor explorative capacity while enhancing the searching capability to solve optimization problems. With the help of the RAV-WO, the proposed AND-TCN consider the features and symptoms of the RA for detecting the RA which permits the better management of the patients.

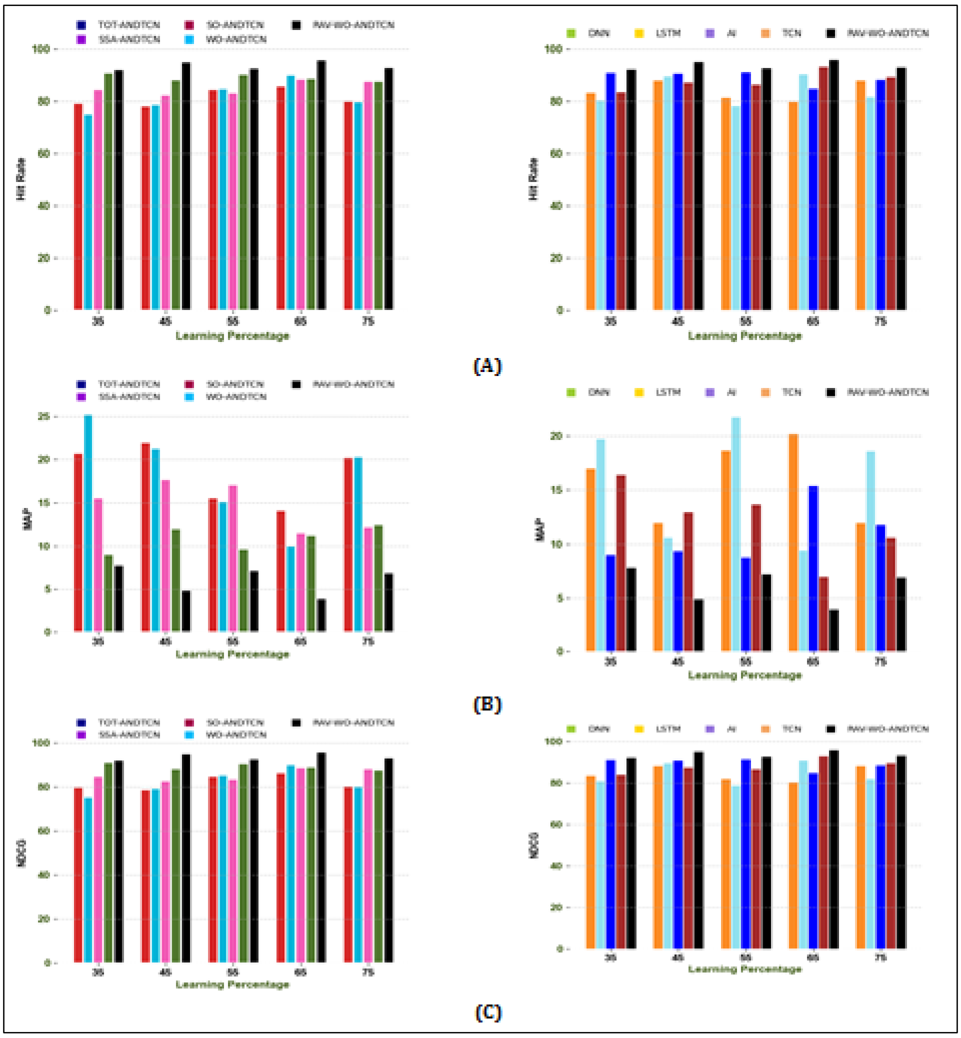


Figure 9: Performance Validation of the RA Recommendation Model in terms of **(A)** Hit rate, **(B)** MAP, **(C)** NDCG

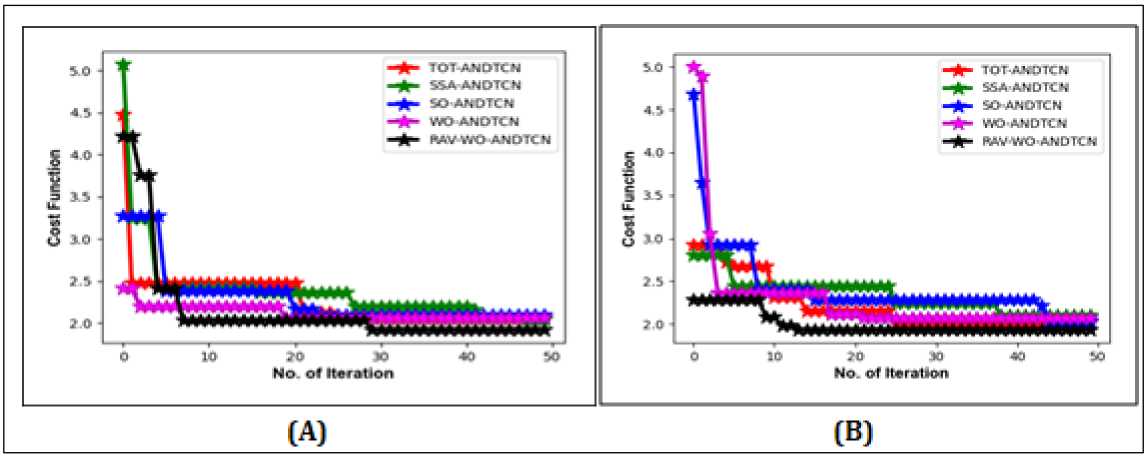


Figure 10: Convergence Assessment of the Proposed Model for **(A)** Response Prediction, **(B)** RA Classification

Accuracy Analysis of the Proposed Model

To determine the effects of the proposed AND-TCN in the RA classification, the epoch count is varied from 100 to 500 is given in Table 2. The results showed that the suggested AND-TCN model attained an accuracy of 92.4% in the RA classification whereas the conventional models such as AI, TCN, CNN and LSTM models attained an accuracy of 74.88, 84.64, 88.64, and 89.2 in the RA classification. These results clearly showcase the performance of the AND-TCN model is better than the other algorithms in the task of the RA classification. The suggested AND-TCN model detects the RA at an earlier stage facilitates the daily activities of humans and also enhances their quality of life.

Table 2: Accuracy Assessment of the Proposed Ra Classification

Epoch	**TOT-ATG-LSMSA (32)**	**SSA-ATG-LSMSA (33)**	**SO-ATG-LSMSA (34)**	**WO-ATG-LSMSA (26)**	**RAV-ATG-LSMSA**
100	74.08	76.24	79.52	90.96	92.4
200	87.84	80.48	85.84	87.92	91.6
300	83.6	79.04	86.16	84.96	91.36
400	78.48	84.64	82.24	88.4	88.4
500	83.52	80.24	87.04	89.44	92.64
Epoch	AI (7)	TCN (31)	CNN (25)	LSTM (28)	RAV-ATG-LSMSA
100	74.88	84.64	88.64	89.2	92.4
200	89.04	84.48	90	89.6	91.6
300	80.24	85.92	90.88	91.2	91.36
400	83.36	81.76	81.84	84.64	88.4
500	86.64	82.64	88.24	87.6	92.64

Conclusion

The user interface of the chatbot is easily utilized by all users. In this work, the ATG-LSMSA-based chatbot system is developed for properly maintaining the RA. The possibility of severe damage to the health condition is prevented by this model. Then the data attained from the response prediction is given to the AND-TCN for classification and recommendation to the RA. It can be agreed from Fig. 7 that the suggested ATG-LSMSA reaches accuracy from 90.6 to 94.9 when varying the K fold from 1 to 5. In addition, the results showed that the suggested AND-TCN model attained an accuracy of 92.4% in the RA classification whereas the conventional models such as AI, TCN, CNN and LSTM models attained an accuracy of 74.88, 84.64, 88.64, and 89.2 in the RA classification. There are several limitations of this study despite its promising results. First, the assessment was based on a dataset from one institute without external validation and might not be generalizable. Second, the influx of alien self-reported questionnaires introduces possible biases and variance in symptom reporting. Lastly, the system currently only processes text-based data and does not include multimodal clinical signals such as imaging or laboratory features. Finally, the real-time validation with rheumatologists was not done and may impact immediate clinical application. These limitations will be addressed by future work. Future work will go on in three main directions: (a) validate the model over multi-center and bigger-scale clinical datasets to increase robustness; (b) extend the system to support multimodal data sources, including radiographic images, biomarkers, and wearable sensor data; and (c) build a mobile application for improving access of patients to disease monitoring and real-time assessment. Such improvements will broaden the translational capabilities of the proposed framework and impact precision rheumatology. Men to Men LILW Model the mobile helper is planned to be included in the model for better use among different patients.

Abbreviations

AND-TCN: adaptive nested dilated temporal convolutional network, ATG-LSMSA: adaptive trans-generative LSTM with sparse multiscale self-attention, CSI: critical success index, DMARDs: disease-modifying antirheumatic drugs, LSTM: long short-term memory, NLP: natural language processing, RA: rheumatoid arthritis, RAV-WO: revised arbitrary variable–based wombat optimization, SER: sentence error rate, SMSA: sparse multiscale self-attention, TCN: temporal convolutional network, WER: word error rate.

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Author Contributions

Bhavani M: conceptualization, methodology design, implementation of the models, experiments, data analysis, manuscript drafting, Prithi Samuel: supervision, guidance on research design and methodology, critical review, editing of the manuscript, validation of results. Both authors have read and approved the final version of the manuscript.

Conflict of Interest

The authors declare no competing financial interests.

Declaration of Artificial Intelligence (AI) Assistance

Generative AI tools (such as ChatGPT) were used to assist in language refinement, rephrasing for clarity, checking grammar, and supporting reference research during the preparation of this manuscript. All references included were verified by the authors from original sources before citation. The authors confirm that all content, analysis, and conclusions were developed by the authors themselves, who reviewed and approved every section. The authors take full responsibility for the integrity and accuracy of the final version of the manuscript.

Ethics Approval

This study did not involve human participants or identifiable patient data; ethics approval and consent were not required.

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