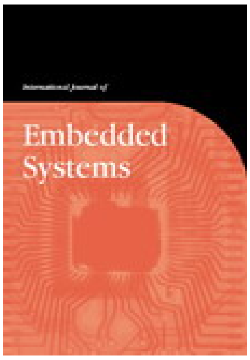

International Journal of Embedded Systems

ISSN online: 1741-1076 - ISSN print: 1741-1068
https://www.inderscience.com/ijes

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DOI: 10.1504/IJES.2024.10068412

Article History:

Received:	21 March 2024
Last revised:	18 September 2024
Accepted:	31 October 2024
Published online:	10 February 2025

Empowering immediate healthcare insights: a deep learning chatbot with modified-CNN and SA-MGO optimisation

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Abstract: This article proposes a novel deep-learning framework designed to empower a highly efficient chatbot, capable of delivering immediate responses to patients seeking information about their medical conditions before their doctor's appointment. The core of the proposed model features a modified-CNN, which incorporates enhancements through the integration of a Gaussian kernel (GK), generalised divisive normalisation (GDN) layer, and the fast Fourier transformer (FFT) for improved feature learning performance. The dataset pre-processed is fed into the modified CNN for effective information extraction. To enhance the optimisation process, the self-adaptive mountain gazelle optimiser (SA-MGO) algorithm is employed, contributing to the overall efficiency of the modified CNN by fine-tuning the parameters of the M-CNN like learning rate, epoch, momentum, and batch-size. The integration of the SA-MGO algorithm further enhances the overall performance of the modified CNN, making the chatbot a valuable resource for individuals seeking immediate insights into their health concerns.

Keywords: chatbot; modified convolutional neural network; generalised divisive normalisation layer; fast Fourier transformer; FFT; self-adaptive mountain gazelle optimiser.

Reference to this paper should be made as follows: Rathee, S., Mehta, S., Yadav, A., Dhand, G., Mohanty, S.N., Garanayak, M. and Paikaray, B.K. (2024) 'Empowering immediate healthcare insights: a deep learning chatbot with modified-CNN and SA-MGO optimisation', *Int. J. Embedded Systems*, Vol. 17, Nos. 3/4, pp.267–284.

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1 Introduction

In the recent surge of interest in human-chatbot relationships (HCR), social chatbots are becoming more prevalent. There is little knowledge about the development of HCRs, although they may impact the broader social context (Skjuve et al., 2021). Artificial intelligence (AI) is gaining attention from business leaders today. As a primary AI tool, chatbots have seen frequent use to support customer service and enable communication between machines and humans (Wang et al., 2022; Rasmussen et al., 2023). With the help of AI, the way humans can understand each other and respond within chatbot systems (Tam et al., 2023) can be improved. The implication and challenges of AI-powered chatbots (AI-chatbots) in the medical domain have become important points of research. ChatGPT represents a significant advancement in AI chatbot technology. Its ability to hold detailed conversations and perform well on tests is impressive. However, it is essential to be aware of its limitations and ensure responsible usage (Han et al., 2022). Specifically, informatics, management and marketing, media and communication science, linguistics and philosophy, psychology and sociology, engineering, design, and human-computer interaction are the major fields utilising chatbots (Følstad et al., 2021).

AI-powered medical chatbots have advanced significantly in recent years, providing several advantages to patients and healthcare practitioners. These chatbots can offer round-the-clock assistance, allowing users to seek medical advice and information at any time, even outside regular clinic hours. AI chatbots can provide initial evaluations or suggestions by asking users a series of questions about their symptoms and medical background, helping users determine whether they need to seek emergency medical assistance and how serious their ailment is (Aminizadeh et al., 2024).

In recent decades, AI systems, in association with natural language processing (NLP) approaches and deep learning methods, can interact with users, understand their needs, map their preferences, and recommend appropriate actions with no human intervention (Pham et al., 2022). The chatbot utilises a NLP system, falling under the umbrella of AI. Therefore, the authors developed an English conversation chatbot using the dialogflow platform as the AI engine (Muhammad et al., 2020). In machine learning (ML), a massive amount of streaming data is needed for the algorithm to train on its own (Santos et al., 2022). There is a drawback in the design and development of these chatbots, as they have built-in AI, NLP, programming, and conversion services (Najm et al., 2020).

ML techniques are utilised to comprehend and handle user-provided natural language input. Chatbots can understand user questions, collect pertinent information, and provide relevant responses using NLP algorithms (Esteva et al., 2017). NLP tasks are very advanced due to computational intelligence techniques like neural networks and deep learning, enabling chatbots to comprehend context, sentiment, and intent more precisely.

In healthcare, the utilisation of AI for medical image analysis has garnered significant attention. Notable studies by Esteva et al. (2017) and Litjens et al. (2017) have demonstrated the efficiency of deep learning algorithms in detecting skin cancer and breast cancer from medical images, respectively. These studies underscore the critical role of ML in augmenting diagnostic capabilities and improving patient outcomes.

The convenient features of chatbots include sending lecture materials in the form of messages to students, as if it were just a chat with a friend (Huang and Chueh, 2021). The availability of chatbots helps students improve their conversation skills. Financial institutions not only answer customer queries but should also clarify customer complaints and provide solutions (Arora et al., 2024). Chatbots are typically used in dialog systems for various practical purposes, including customer support or knowledge retrieval (Jothi et al., 2013). For this purpose, financial institutions and many banks use chatbots to provide solutions to customer complaints and queries. Chatbots store a variety of answers and user feedback (Abedin, 2021; Carlander-Reuterfelt et al., 2020). The main contributions of the paper are as follows,

- Introducing a modified CNN as the core of the proposed model, featuring enhancements such as the integration of a GK, GDN, and the FFT. These modifications aim to improve the feature learning performance of the model.
- Utilising the SA-MGO algorithm to enhance the optimisation process of the modified CNN. The SA-MGO algorithm contributes to the overall efficiency of the model by fine-tuning key parameters such as learning rate, epoch, momentum, and batch size.
- Demonstrating that the integration of the SA-MGO algorithm significantly enhances the overall performance of the modified CNN. This improvement contributes to making the chatbot a valuable and efficient resource for individuals seeking immediate insights into their health concerns.

The paper is arranged as follows: Section 2 examines existing research on chatbots. Section 3 provides a full description of the proposed methodology; Section 4 compares the findings obtained with the suggested model to those obtained with existing methods; and Section 5 offers a thorough conclusion.

2 Related work

In this section, the recent existing papers related to the chatbot are discussed.

The deep feedforward multilayer perceptron-based AI chatbot interaction and prediction model has been presented by Chakraborty et al. (2022). A knowledge vacuum regarding theoretical standards and useful advice for developing AI chatbots was uncovered in the investigation. Additionally, a quick comparison has been shown for testing accuracy and time complexity. In this work, a minimum loss of 0.1232 and a maximum accuracy of 94.32% was achieved. Pradeep et al. (2022) have introduced the Med Bot, an automated system based on AI that leverages ML and NLP to create a personalised virtual assistant that can answer questions about medical devices. It takes the position of technical support specialists in understanding the unique characteristics and functionalities of the medical equipment, which is frequently more difficult to use.

Creating and deploying 'FLOKI', a chatbot has been designed to help maritime trainees understand collision avoidance regulations (COLREGs). IBM Watson Assistant, a cognitive computing tool that makes use of Application Programming Interfaces (APIs) in its cloud server, was used in the chatbot's design (Sharma et al., 2023). The training of COLREGs was chosen as a use case in the study, which aimed to demonstrate the implementation of the AIEd tool.

Denecke et al. (2021) have recommended the chatbots, or systems designed to converse with users, based on AI, which provides ability for people to comprehend one another and respond appropriately. The user's query is comprehended by the bot, which then generates an accurate response. Within the field of healthcare, these chatbots-based systems are becoming more and more popular because of their potential to improve patient adherence to electronically delivered treatments and illness management initiatives.

Khadija et al. (2021) have proposed a general architecture for an AI-powered health chatbots. A deep learning-based component is used, whose job it is to provide appropriate responses based on pre-formatted data, with the dialogue and communication parts of natural language generation and understanding (NLU and NLG). Deep learning techniques that helped in the creation of dataset, and the way the expert core engine retrieves the relevant data.

A comprehensive evaluation of the literature was conducted by the authors based on 386 publications found in the Web of Science database. The various papers identify the conceptual framework and research trends, with the goal of recommending a future study agenda. Major papers and research subjects were examined by the intellectual structure, and via keyword analysis (Nimal et al., 2023).

The feasibility and efficacy of using an AI-based chatbot to improve smile and speech has been discussed by the research (Ogawa et al., 2022). The potential predictive value of objective face and speech parameters has been explored for motor symptoms, cognition, and mood. There is a series of facial and conversational voice samples from 20 PD patients during weekly teleconsultation sessions for five months as part of an open-label randomised trial.

Santos et al. (2022) have introduced the chatbot management process, a technique for managing content on chatbot platforms. The suggested approach is founded on the lessons learned during the creation of the chatbot Eva speak for the Brazilian Virtual School of Government. With the use of user interaction analysis, this methodology aims to evolve chatbot content in a cyclic process under human supervision. The suggested process was broken down into three separate stages: manage, build, and analyse. Furthermore, the tasks of the chatbot team are clearly defined by the suggested technique.

Meshram et al. (2021) represents a significant advancement in automation by decreasing human interaction and handling repetitive operations effectively. Chatbots have uses in a variety of industries, including education, healthcare, and business. Their research examined multiple publications, investigating various chatbot forms and their pros and cons. The data show that chatbots are extremely adaptable, providing accuracy, independence from human resources, and 24/7 availability.

Lin et al. (2024) proposed a multiparty secure inference scheme with an adaptive number of parties. The scheme can perform secure inference with a two-thirds honest majority setting when no parties are involved. They also evaluated the scheme's security and performance; their empirical results demonstrate that the scheme still has practicality even when extended to more parties. Moving forward, they intend to design a more efficient online phase by shifting some calculations from online to offline, improving the overall experience of using secure inference services. Formal security analysis proves that the scheme achieves malicious security in the honest-majority setting, and extensive experiments demonstrate that this scheme reduces communication costs by about 30% in large neural networks compared with previous solutions.

Feng et al. (2021) proposed the work that presents the first blockchain-enabled tensor-based conditional deep convolutional GAN model for cyber-physical-social systems. The model employs blockchain technology to tackle the reliability challenges of the TCDC-GAN model. The TCDC-GAN model specifically builds for multipart scenarios where cyber-physical-social data are gathered from manifold providers. The TCDCGAN model employs a tensor model for its construction. The images produced from the experiment results display similarities to the photos from the datasets, and it can be challenging to differentiate them.

To solve the data silos issue in distributed ML with privacy leakage, and privacy-preserving federated learning (PPFL), Zhang et al. (2023) proposed a secure and communication-efficient FL scheme using improved compressed sensing and CKKS homomorphic encryption. They implement a lossy compression of the model by using discrete cosine transform, then use CKKS homomorphic encryption to encrypt the data transmitted between clients and centre servers due to its high efficiency and support for batch encryption. Formal security analysis proves that the scheme is secure against indistinguishability under chosen plaintext attacks, and extensive experiments demonstrate that the scheme achieves high accuracy at a 0.05% compression rate.

According to Feng et al. (2023), the RNN model's unprecedented growth has encountered heterogeneous IoT data and privacy issues. The existing RNN model can not deal with heterogeneous sequential data; the larger datasets used in training the RNN model often contain sensitive information. To handle these challenges, this research proposes a novel differentially private tensor-based RNN (DPTRNN) that can be applied in many challenging deep learning sequence tasks for IoT systems. Specifically, they proposed a tensor-based RNN model to process heterogeneous sequential data. To guarantee privacy, they develop a tensor-based back-propagation through time algorithm with perturbation to avoid exposing sensitive information for training the tensor-based RNN model within the differential privacy framework. Thorough security analysis shows that the differential private tensor-based RNN efficiently protects the confidentiality of sensitive user information for IoT.

2.1 Problem statement

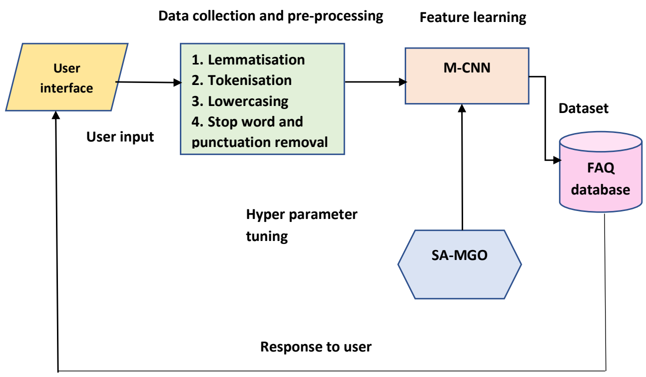
The current state of AI chatbot development, as highlighted in the existing literature, reveals a notable gap in both theoretical standards and practical guidance. While several studies showcase innovative applications, ranging from personalised virtual assistants in healthcare to educational tools for maritime trainees, a unified understanding of fundamental principles for creating effective and adaptable AI chatbots is lacking. The comparison of proposed models typically focuses on metrics like testing accuracy and time complexity, leaving critical aspects such as user experience and ethical considerations unexplored. Additionally, the popularity of healthcare-focused chatbots underscores the need for a more in-depth exploration of challenges and opportunities in implementing such systems across various real-world scenarios. Furthermore, while some studies propose specific architectures, a comprehensive evaluation of the broader conceptual framework and research trends in the field is essential. Addressing these gaps is crucial for advancing AI chatbot technology to ensure it is not only effective and adaptable but also ethically grounded for diverse applications, ultimately enhancing the quality of human interaction with these intelligent systems.

3 Proposed methodology

The proposed methodology entails a comprehensive approach to empower a highly efficient chatbot for immediate medical information delivery as in Figure 1.

Commencing with the collection of a diverse medical dataset, rigorous pre-processing involves removing noise through stop words and punctuation removal, lemmatisation, text case normalisation, and tokenisation. The core of the model lies in the M-CNN, enhanced with a Gaussian kernel (GK), generalised divisive normalisation (GDN) layer, and fast Fourier transformer (FFT) for optimal feature learning. The optimisation process is fine-tuned using the SA-MGO algorithm, adjusting critical parameters. Training on a split dataset is followed by integration into a user-friendly chatbot interface. Evaluation metrics and user feedback guide iterative fine-tuning, ensuring the ability to deliver immediate, accurate responses to patients inquiring about their medical conditions before scheduled appointments.

Figure 1 Block diagram of the proposed chatbot model (see online version for colours)



Algorithm

Input: FAQ dataset

Output: Interactive chatbot

1 Collect the required data and pre-process the data
  1 Lemmatisation
  2 Tokenisation by using the function tokenise()
  3 Lowercasing
  4 Stop word and punctuation removal.

2 Enhanced feature learning using M-CNN
  1 Apply the convolution process by using the equation
  $$y^{l(i,j)} = K_i^l * x^{l(r^j)} = \sum_{j=0}^{W} K_i^l(j') X^{l(j+j')}$$
  2 Transformation using max-pooling by
  $$P^{l(i,j)} = \max_{(j-1)W+1 \leq tjW} \{a^{l(i,t)}\}$$
  3 Apply FFT using
  $$X_k = \sum_{n=0}^{N-1} x_n e^{-2\pi kn/N}, k = 0, \ldots, N-1$$
  4 Speed up the learning using
  $$w_i^k(m,n) = \frac{v_i^k(m,n)}{\sqrt{\beta_i^k + \sum_j \gamma_{ij}^k (v_j^k(m,n))^2}}$$
  5 Convert to 1D array.
  6 Apply to the FC layer
  7 Use softmax activation
  $\mathcal{L}_{softmax} = -\sum_{s\in S}\sum_{i=1}^{N} \omega_{yi} y_i \log(\hat{y}_i)$ to predict the metaphor label sequences.

3 Tune the hyperparameter using SA-MGO

4 Gather the user responses and analyse.

5 Show the prediction output in the chatbot interface

3.1 Data collection and pre-processing

The dataset which is utilised in this proposed model is collected from Kaggle.com. The dataset has a total of 4,920 rows and 133 columns out of which 132 were symptoms and the last column is the prognosis. The total number of diseases is 42 such as aids, dengue, malaria, etc.

The dataset is carefully pre-processed in order to make it ready for the improved deep learning-based model. Lemmatisation is the process of standardising words to their basic forms once stop words and punctuation are removed. Tokenisation divides the pre-processed text into a string of words, generating a structured format, and normalising the text case through lowercase conversion guarantees consistency. By combining these techniques, the dataset is improved and made more suitable for the M-CNN (Mahmoud et al., 2018).

3.1.1 Lemmatisation

Lemmatisation and stemming are comparable processes, but lemmatisation better maintains the term's meaning. The word that is reduced to its basic form is lemma, which keeps the meaning and semantics of the word. The difference between lemmatisation and stemming is demonstrated by the terms 'bullying' and 'bullied', which are stemmed as 'bulli', but become 'bully' when lemmatised. Sometimes lemmatisation is favoured over stemming since the word's meaning is preserved.

3.1.2 Tokenisation

The process of breaking up complex content, such as paragraphs, into manageable chunks known as tokens is known as tokenisation. There are two groups,

- Sentence tokenisation: The tokenise() function may be utilised to segment a paragraph into a list of phrases.
- Word tokenisation: The tokenise() function may be utilised to separate a statement into a list of words. Activate every library required to perform tokenisation on the supplied data.

3.1.2.1 Sentence tokenisation

Dissecting a text paragraph into its constituent phrases is necessary. The punctuation used in English and other languages to denote sentences and paragraphs makes this task easier: commas and full stops. The process is not straightforward, though, as English abbreviations also use the same symbol.

3.1.2.2 Word tokenisation

Word tokenisation, sometimes called word segmentation, is the act of breaking down a text paragraph into its individual words. When delimiters like word space are used in certain languages, like English, it might be easy to tell when a new word is beginning. However, compound words employ the same spaces, making the process much more difficult.

3.1.3 Lowercasing

The reason behind the text in lowercase is important because the computer might read the same word twice if it is written in capital letters or in a different font style. The terms 'LOVE' and 'love' may be seen differently and assigned different vectors, for example, when the text is vectorised for feature extraction. Despite being the simplest and most efficient pre-processing method that maximises the chance of accurate results, this step is sometimes disregarded.

3.1.4 Stop word and punctuation removal.

The pre-processing method that is most used in different NLP applications is stop word removal. Simply removing phrases that appear often in all corpus texts is the goal. Pronouns and articles are common stop words. Stop words, such as 'a', 'an', 'the', 'in', 'has', and so on, are frequently found in languages. Punctuation like comma just add meaning to sentence and must be filtered from text as they have no more importance.

3.2 Enhanced feature learning using M-CNN

CNN is a multi-stage neural network consisting of one classification step and several filter stages. The core component of the suggested system for effective information extraction from patient questions is the M-CNN. With significant changes for better feature learning, the M-CNN is enhanced to meet the needs of the medical sector. To improve the network's capacity to detect minute patterns and subtleties in medical text data, a GK is integrated into the architecture. Further refining the normalising process and enhancing the network's performance is the GDN layer. To improve feature learning and help the model identify complex correlations in the medical data, the FFT is presented as a useful component (Subha and Sathiaseelan, 2023). This customised design places the M-CNN as a strong and specialised component, essential to the ability to analyse medical questions and provide patients with timely and accurate responses. It does this by fusing classic CNN principles with some innovative improvements. The overall design of a CNN is shown in Figure 2, with the layers.

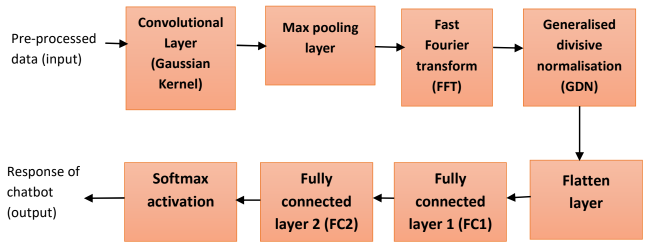
3.2.1 Convolutional layer

To produce the output features, the activation unit convolves the input local regions with GKs in the convolutional layer before the activation unit. Weight-sharing is the term used in the literature to describe the process by which each Gaussian filter extracts the local characteristics of the input local region using the same kernel. In the next layer, one filter is equivalent to one frame; the quantity of frames is referred to as the layer's depth. The weights and bias of the i^{th} filter kernel in layer l are shown by K_i^l, while the j^{th} local region in layer l is indicated by $x^{l(r^j)}$. Consequently, this is how the convolution process is explained,

$$y^{l(i,j)} = K_i^l * x^{l(r^j)} = \sum_{j=0}^{W} K_{j=0}^{W} K_i^l \left(j' \right) X^{l(j+j')} \quad (1)$$

where $K_i^l(j')$ represents the j^{th} weights in frame i of layer (l + 1), and the notation * signifies the dot product of the kernel and the local regions. W denotes the kernel's width.

Figure 2 Structure of the M-CNN (see online version for colours)



3.2.2 *Max pooling layer*

A pooling layer is typically placed after a convolutional layer since it decreases the spatial size of the features and speeds up the learning process. There are several kinds of pooling functions; the most widely used one is max pooling. With a certain kernel/pool size, the max pooling layer accumulates location-invariant features by executing the local max operation across the input features. The max-pooling layer may efficiently minimise the number of parameters, memory use, and computation due to a huge amount of trained 2D image data (to limit the danger of overfitting). Only the maximum input value of each receiving field can get through to the next layer network once the pooling layer has determined the size and stride of the receiving field; all other inputs are deleted. The max-pooling layer not only lowers the number of parameters, memory utilisation, and computation but also adds a level of invariance for tiny changes. The transformation known as max-pooling is explained as:

$$P^{l(i,j)} = \max_{(j-1)W+1 \le t j W} \left\{ a^{l(i,t)} \right\} \tag{2}$$

3.2.3 *FFT*

The number of calculations required for N points can be decreased from $O(N^2)$ to $O(N\log N)$ using the FFT discrete Fourier transform technique. This strategy can save more processing resources as the number of sample points increases. First, applying a sliding window obtains n consecutive time-domain data from the original signal. Then, using the FFT method – which is defined as – each window data is converted to frequency information.

$$X_k = \sum_{n=0}^{N-1} x_n e^{-2\pi kn/N},\ k = 0, N-1 \tag{3}$$

In this case, X_k represents time-domain data, while x_0, …, x_{N-1} are complex numbers. The sample point count is denoted by N.

3.2.4 *GDN*

A GDN layer is added to lessen the change in interval covariance and speed up learning with less computational burden. It is often inserted either directly following the convolutional layer or prior to the activation function layer. There is a GDN procedure after every convolution layer. The GDN conversion is best explained as,

$$w_i^k(m,n) = \frac{v_i^k(m,n)}{\sqrt{\beta_i^k + \sum_j \gamma_{ij}^k \left(v_j^k(m,n)\right)^2}} \tag{4}$$

In this case, (m, n) represents the geographic position of a particular value of a tensor (such as V^K, and i and j run across channels.

3.2.5 *Flatten layer*

The output of the preceding layers is transferred for flattening after passing through the convolution and pooling layers and prior to entering the fully connected layers. This means that the input array's dimensions from earlier stages are combined into a single, huge dimension.

3.2.6 *Fully connected layer*

Every output of the layer preceding the FC layer that anticipates the picture label is coupled to every one of its inputs. Two FC levels are provided in this study. This layer uses activation algorithms like sigmoid, softmax, and others to predict the target class. The softmax function is used in the output layer of multi-classification models to return the probabilities of each class that has a higher possibility of being the target class. A way to compute discrete probability distributions over several classes is provided by the Softmax function; the probabilities sum up to one.

3.2.7 *Softmax activation function*

In each convolutional block, the activation function layer is essential. By enabling the network to describe the input signal in a nonlinear way, it improves representation and increases the distinguishability of the learnt features. Many activation functions are available for usage; ReLU, Identity, Tanh, and Sigmoid are among the most often utilised. We use a thick layer with a Softmax activation function to predict the metaphor label sequences. The loss function of our model is created in the following way due to the cost-sensitive cross entropy:

$$\mathcal{L}_{softmax} = -\sum_{s \in S} \sum_{i=1}^{N} \omega_{y_i} y_i \log(\hat{y}_i) \tag{5}$$

where the projected value is y_i, the label for the i^{th} position is $\hat{y}_i$, and the loss weight is ω_{y_i}.

3.3 *Hyperparameter tuning using SA-MGO*

An essential component and architecture of the chatbot is the SA-MGO algorithm, which optimises the M-CNN's performance. This optimisation approach raises the M-CNN's overall efficiency by dynamically adjusting important parameters during training, a behaviour inspired by the adaptable behaviour of mountain gazelles. The learning rate, epoch, momentum, and batch size are among the crucial parameters that the SA-MGO algorithm is highly utilised for optimising.

Algorithm

1 Randomly initialise the population of gazelles randomly
2 Evaluating the fitness of each gazelle
3 While termination criterion is not fulfilled do
    1 Evaluate the fitness of each and every gazelle
    2 Adapt exploration and exploitation parameters
    3 Update positions of gazelles
    4 Simulate predator mechanism for diversity
    5 Select the best-performing gazelles
    End while
4 Return the best solution found

With the SA-MGO method, the M-CNN's optimality and convergence speed are improved by dynamically modifying these parameters according to the changing features of the optimisation landscape. With adaptive optimisation-CNN is continuously fine-tuned, allowing it to provide patients with rapid and accurate answers to questions about their medical problems (Kumar and Sharma, 2023).

The Arabian Peninsula and its environs are home to the mountain gazelle, one of the species of gazelle. Its population density is rather low despite its wide distribution range. The species has a tight relationship with the Robinia tree species' environment. Because they are very protective of their territory, mountain gazelles keep a considerable space between them. Mother-offspring herds, young male herds, and lone males with their territories are the three categories into which they may be divided (Heidari et al., 2024). Regular fights between male gazelles take place over resources; these fights are not as spectacular as those involving females. When fighting, immature males utilise their horns more frequently than territorial or adult males.

We tune the hyperparameters such as learning rate = 0.0001, epochs = 150, momentum = 0.10, and batch size = 465 for getting the better accuracy of the model (99.73%).

3.3.1 Mathematical model of MGO

The MGO optimisation algorithm is based on a mathematical model that considers important facets of the social behaviour and habitats of mountain gazelles, such as the behaviour of territorial and solitary males (TSM), maternity herds (MH), bachelor male herds (BMH), and migration patterns in search of food (MSF). Here is how they are mathematically modelled.

3.3.2 Fitness calculation using opposition-based learning

Individual fitness is calculated using the OBL technique, which then compares it against the opposite number and advances the better result to the next iteration. OBL strategy has the following definition:

3.3.2.1 Opposite number

Let x be a real number such that $x \in [l_b, u_b]$. Then, equation (6) gives the opposite number $\bar{x}$,

$$\bar{x} = u_b + l_b - x \tag{6}$$

where the terms upper bound and lower bound are denoted by u_b and l_b, respectively.

3.3.2.2 Opposite vector

The calculation of $\bar{x}_i$ may be done as follows if $x = (x_1, x_2, \ldots, x_D)$ where $x_1, x_2, \ldots, x_D$ are real values and $x \in [l_b, u_b]$:

$$\bar{x}_i = l_b(i) + u_b(i) - x_i \tag{7}$$

If $f(\bar{x}) < f(x)$, then $\bar{x}_i$ will ultimately put the present solution.

3.3.2.3 TSM

The process by which adult mountain gazelles establish and defend their territories through combat is represented into equation (8) as follows.

$$TSM = M_C - \left|\left(r_1 * BH - r_2 * X_{i,j}^t\right) \times F\right| Cof_r \tag{8}$$

where MH, F, and Cof_r are the best cheetah, constant and the coefficient vector respectively. The values of the BH, F, and Cof_r are provided in equations (9), (10) and (11), respectively. r_1 and r_2 are random numbers 1 or 2, which represents the male Cheetah's (M_C) position vector of the global solution.

$$BH = X_{range} \times r_1 + M_{pr} \times r_2, \, range = \left\{\frac{N}{3}, \ldots, N\right\} \tag{9}$$

A random solution in the range is X_{range}, which is a young guy. The average number of randomly chosen search agents is called M_{pr}. N is the number of gazelles, while r_3 and r_4 are random numbers between 0 and 1.

$$F = N_1(D) \times \exp\left(2 - Iter \times \left(\frac{2}{Max_{iter}}\right)\right) \tag{10}$$

where $Iter$ is the iteration counter, whereas Max_{iter} indicates the maximum iterations. N_1 is a random number in the problem space that is calculated using a standard distribution. Equation (10) uses equation (12) to compute the value of a. Additionally, r_3 and r_4 are random numbers chosen between 0 and 1. The problem dimension is represented by the random integers N_2, N_3, and N_4, which are located in the search space's typical range.

$$Cof_r = \begin{cases} (a+1)+r_3 \\ a \times N_2(D) \\ r_4(D) \\ N_3(D) \times N_4(D)^2 \times \cos\left((r_4 \times 2) \times N_3(D)\right) \end{cases} \tag{11}$$

$$a = -1 + Iter \times \left(\frac{-1}{Max_{iter}} \right) \tag{12}$$

3.3.2.4 MH

Iter and Max_{iter} stand for the iteration counter and maximum iterations, respectively, whereas N_1 is a random value in the issue dimension that is calculated using a standard distribution. Furthermore, r_3 and r_4 are random values taken from a range of 0 to 1. The random numbers N_2, N_3, and N_4 have the problem dimension and are located inside the search space's typical range. Equation (13) is utilised to compute the MH value,

$$MH = (BH + Cof_r) + (r_3 \times male_{gazelle} - r_4 \times X_{rand}) \times Cof_r \tag{13}$$

A gazelle's random vector location throughout the population is represented by X_{rand}, and two random numbers r_3 and r_4, are chosen from either 1 or 2.

3.3.2.5 BMH

When they reach adulthood, young adult males mark out their territories and fight with adult males to win the female gazelles. This is expressed in the form of equation (14).

$$BMH = \left(X_{i,j}^t - D\right) + (r_7 \times M_C - r_8 \times BH) \times Cof_r \tag{14}$$

The gazelle's position vector for the current iteration is denoted by $X_{i,j}^t$, and the numbers r_7, and r_8 are either 1 or 2. Equation (15) is used to calculate D, and r_8 is a number chosen at random from the range of 0 to 1.

$$D = \left(\left|X_{i,j}^t\right| + |M_C|\right) \times (2 \times r_6 - 1) \tag{15}$$

3.3.2.6 MSF

Mountain gazelles travel great distances in search of food on a constant basis. Equation (16) below models this arbitrary movement.

$$MSF = (u_b - l_b) \times r_7 + l_b \tag{16}$$

where r_7 is a randomly chosen number (0, 1) and l_b and u_b represent the lower and upper boundaries of the search space, respectively.

In our proposed model the SA.MGO optimiser outperforms standard optimisers in the Medckbot framework by leveraging the self-attention (SA) mechanism to focus on the most relevant features, reducing redundancy and enabling parallel processing. This enhances feature extraction and speeds up computations. Additionally, the MGO component simultaneously optimises multiple objectives, efficiently exploring the search space and reducing unnecessary computations. The integration of these techniques leads to faster convergence, balanced exploration and exploitation, and better resource management, resulting in improved time and computational complexity in the Medckbot framework.

4 Result and discussion

This section compares the suggested model's outcomes with those of current methods. The implementation is done using the Python platform. 30% of the data is for testing, and 70% is for training. To train the model on one subset and then evaluate its performance on the other subset to see how well it can generalise, a division is required. The suggested medical chatbot algorithm is tested using the mental health FAQ for chatbot dataset. Frequently asked questions regarding mental health are included in this collection. Along with the dataset, some frequently asked questions are included from the Google.

We tune the hyperparameters learning rate = 0.0001, epochs = 150, momentum = 0.10, and batch size = 465 to achieve the accuracy of the model 99.73%.

In this study, we used a 'modified CNN with SA.MGO' to validate the Medckbot model on a very small dataset (97 FAQs, text), with the argument being its capacity to improve feature extraction and optimisation. Modified convolutional neural networks (CNNs) are good at detecting detailed patterns in text data, and the SA mechanism helps focus on the most important sections of the text. Furthermore, multi-objective genetic optimisation (MGO) refines the model parameters, resulting in enhanced performance and generalisation even with minimal data. This combination guarantees that the MedckBot model is validated robustly and accurately.

4.1 Performance metrics

In this section the performance metrics along with the formulae used to calculate the correctness of a record that defined the ratio of accurately identified information to all its data. Precision is the depiction of the total number of real samples that are suitably considered during the classification process by using all the samples utilised in the procedure. The sensitivity value may be obtained by simply dividing the total positives by the proportion of true positive forecasts. To calculate specificity, divide the total number of negatives by the number of correctly predicted negative outcomes. The harmonic means of accuracy and recall rate is the definition of the F-score. The equation which displays the two-by-two binary value association measure, often known as MCC. When all adverse events are divided by all adverse events that were mistakenly classed as positive, the false positive rate (FPR) is obtained (Jindal and Singh, 2019). Commonly referred to as the 'miss rate', this is the likelihood that a genuine good result will be overlooked by the examination.

Table 1 Performance metrics formulas

Performance metrics	*Formulas*
Accuracy	$Accuracy = \frac{TP + TN}{TP + FP + FN + TN}$
Precision	$Precision = \frac{TP}{TP + FP}$
Sensitivity	$Sensitivity = \frac{TP}{TP + FN}$
Specificity	$Specificity = \frac{TN}{TN + FP}$
F-measure	$F_{score} = \frac{2\ precision \times recall}{precision + recall}$
Matthew's correlation coefficient (MCC)	$MCC = \frac{(TP \times TN - FP \times FN)}{\sqrt{(TP + FN)(TN + FP)(TN + FN)(TP + FP)}}$
Negative prediction value (NPV)	$NPV = \frac{TN}{TN + FN}$
False positive ratio (FPR)	$FPR = \frac{FP}{FP + TN}$
False negative ratio (FNR)	$FNR = \frac{FN}{FN + TP}$

4.2 Overall comparison by varying the several parameters

Fine-tuning a CNN entails modifying numerous hyperparameters to improve performance. The self-adaptive mountain gazelle optimiser (SA-MGO) may be used to automate and improve the process by looking for the optimal combination of hyperparameters. In our method we fine-tune hyperparameters like learning rate, epochs, momentum, and batch size. We have achieved the accuracy of the CNN model 99.73% by taking learning rate = 0.0001, epochs = 150, momentum = 0.10, and batch size = 465.

The suggested model's (CNN) performance measures are compared to those of other methods, such as linear SVM, LSTM, and ANN. Table 1 displays the comparison.

The suggested model performs better than the other models when compared on a number of evaluation criteria, including CNN, artificial neural network (ANN), long short-term memory (LSTM), and linear support vector machine (linear SVM). The suggested model performs better than the others, with an accuracy of 99.73%; CNN comes in second, with 98.47%. The suggested model likewise exhibits excellence in terms of precision, sensitivity, and F-measure, with respective values of 99.6%, 99.6%, and 99.6%. Furthermore, the suggested model performs exceptionally well in terms of Matthews correlation coefficient (MCC) at 99.55% and specificity (99.8%). Its FPR of 0.2% and false negative rate (FNR) of 0.4% are particularly noteworthy. To sum up, the model that has been suggested performs remarkably well when compared to conventional CNN, ANN, LSTM, and linear SVM models.

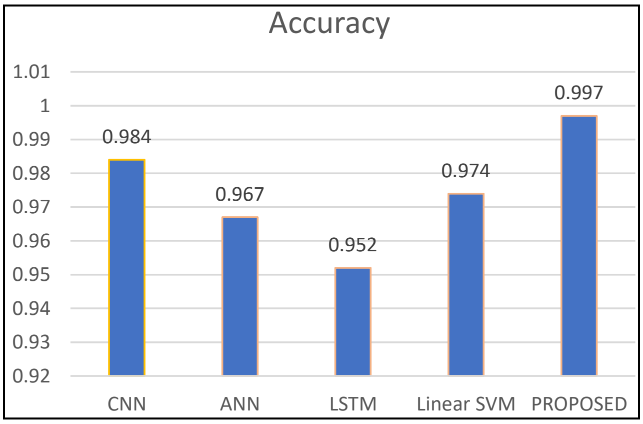
Table 2 Comparison of performance metrics for training 70% and testing 30%

Performance metrics	*CNN*	*ANN*	*LSTM*	*Linear SVM*	*Proposed*
Accuracy	0.984667	0.967333	0.952667	0.974	0.997333
Precision	0.977	0.951	0.929	0.961	0.996
Sensitivity	0.977	0.951	0.929	0.961	0.996
Specificity	0.9885	0.9755	0.9645	0.9805	0.998
F-measure	0.977	0.951	0.929	0.961	0.996
MCC	0.9655	0.9265	0.8935	0.9415	0.9955
NPV	0.9885	0.9755	0.9645	0.9805	0.998
FPR	0.0115	0.0245	0.0355	0.0195	0.002
FNR	0.023	0.049	0.071	0.039	0.004

4.2.1 Accuracy

The accuracy scores in the table show how well each model can categorise instances in the presented dataset. CNN ranked first among the compared models with an accuracy of 98.47%, followed by ANN at 96.73%, LSTM at 95.27%, and linear SVM at 97.4%. With a remarkable accuracy of 99.73%, the suggested model notably beat the others, demonstrating its remarkable capacity for accurate class label prediction. Since accuracy is essentially a comprehensive indicator of a model's overall performance, a greater accuracy indicates a more effective model's ability to provide accurate predictions throughout the whole dataset. The accuracy comparison is displayed in Figure 3.

Figure 3 Comparison of the accuracy metric (see online version for colours)



4.2.2 Precision

Each ML model's capacity to provide precise positive predictions within the dataset is shown by the precision values in the table. 96.7% of CNN's positive forecasts were accurate, according to the network's accuracy score. 95.1% accuracy in recognising positive cases was shown by the ANN, which also had a precision of 95.1%. The accuracy of the positive predictions made by LSTM was 92.9%, indicating its skill in this area. By accurately detecting positive cases, the linear SVM demonstrated its accuracy with a precision of 96.1%. The suggested model was shown to be very accurate in forecasting positive events, as evidenced by its maximum precision of 99.6%, surpassing all other models. The precision comparison is displayed in Figure 4.

Figure 4 Comparison of the precision metric (see online version for colours)

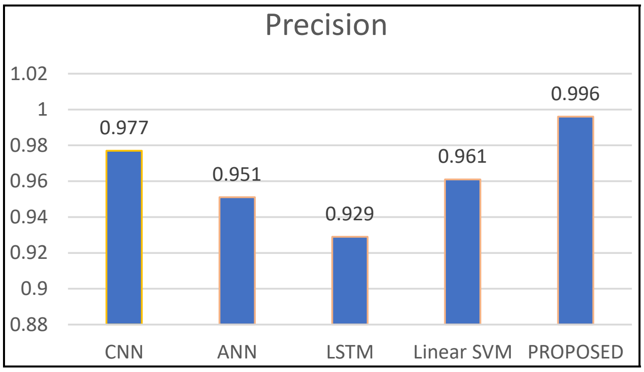
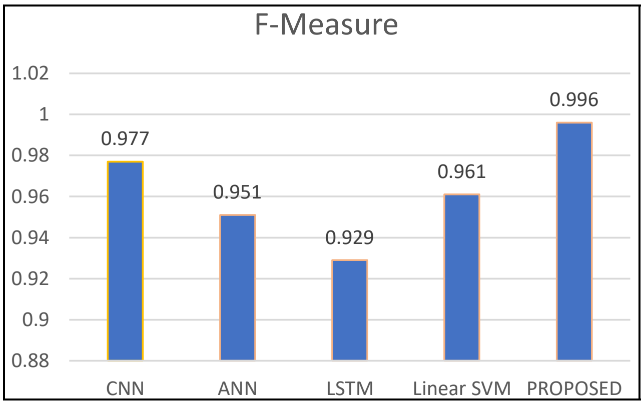


Figure 5 Comparison of the F-measure metric (see online version for colours)



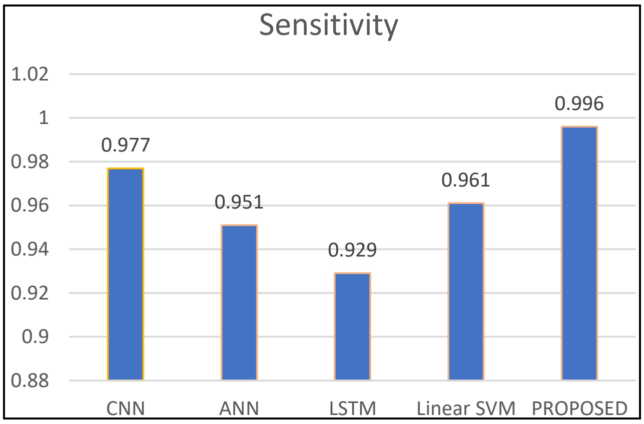
4.2.3 F-measure

The F-measure provides a fair assessment of a model's effectiveness, particularly in situations when the datasets are unbalanced. With an F-measure of 97.7% in the comparison with other models, the CNN showed a balanced combination of recall and accuracy. The ANN performed well overall in terms of recall and precision, coming in second with an F-measure of 95.1%. The LSTM model demonstrated its efficacy in striking a balance between recall and accuracy with an F-measure of 92.9%. With an F-measure of 96.1%, the linear SVM demonstrated a balanced performance. Remarkably, the suggested model achieved the highest F-measure of 99.6%, demonstrating its remarkable capacity to strike a balance between recall and accuracy, which is essential for the overall efficacy of the model. The F-measure comparison is displayed in Figure 5.

4.2.4 Sensitivity

When compared to other models, the CNN's sensitivity was 97.7%, demonstrating its ability to accurately identify 97.7% of real positive cases. Accurately recognising 95.1% of the positive events, the ANN trailed closely behind with a sensitivity of 95.1%.

Figure 6 Comparison of the sensitivity metric (see online version for colours)



The sensitivity of the LSTM model was 92.9%, indicating that it could accurately detect 92.9% of the positive events. A sensitivity of 96.1% was attained by the linear SVM, highlighting its accuracy in detecting 96.1% of the genuine positive cases. The suggested model, in particular, outperformed the others and had the maximum sensitivity (99.6%), highlighting its remarkable capacity to accurately capture 99.6% of the real positive cases. The comparison of sensitivity is displayed in Figure 6.

4.2.5 Specificity

When compared to other models, the CNN had a specificity of 98.85%, which indicates that it was accurate in detecting 98.85% of the real negative cases. With a specificity of 97.55%, the ANN closely trailed, demonstrating its ability to correctly identify 97.55% of the real negative events. With a specificity of 96.45%, the LSTM model demonstrated its efficacy in properly recognising 96.45% of the negative cases. With a specificity of 98.05%, the linear SVM demonstrated its accuracy in detecting 98.05% of genuine negative cases. Surprisingly, the suggested model beat all others with the highest specificity of 99.8%, demonstrating its remarkable accuracy in correctly recognising 99.8% of the real negative cases. Figure 7 compares the specificity.

4.2.6 MCC

When the CNN was compared to other models, it showed an MCC of 96.55%, which means that there was a positive and negative correlation between the CNN's predictions and the actual results. An MCC of 92.65% for the ANN showed a strong connection between expected and actual results, which was followed closely. Given that false positives and false negatives are taken into account, the LSTM model's MCC of 89.35% highlights its connection. A high correlation between expected and actual results was indicated by the linear SVM's MCC of 94.15%. The suggested model, not surprisingly, fared better than any other, having the greatest MCC at 99.55%, demonstrating its remarkable capacity to successfully link predictions with reality. Figure 8 compares the MCC.

Figure 7 Comparison of the specificity metric (see online version for colours)

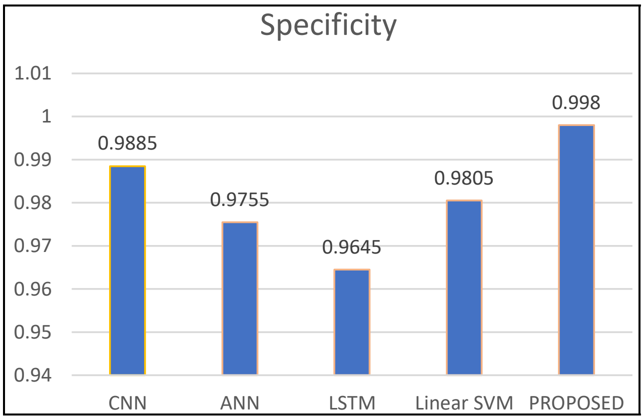
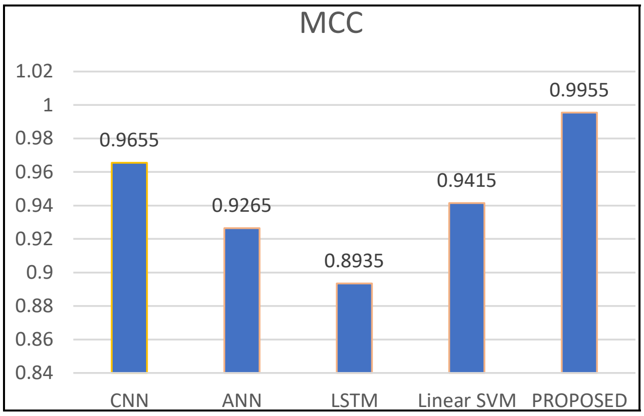


Figure 8 Comparison of the MCC metric (see online version for colours)

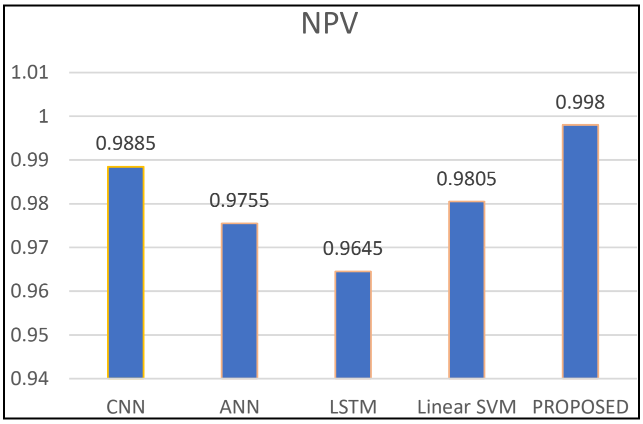


4.2.7 NPV

The CNN exhibited an NPV of 98.85% in the comparison of current models, indicating its accuracy in correctly recognising 98.85% of cases predicted as negative that were in fact real negatives. With an NPV of 97.55%, the ANN closely trailed, demonstrating its ability to accurately identify 97.55% of cases predicted as negative shown in Figure 9.

With a projected negative value (NPV) of 96.45%, the LSTM model demonstrated its accuracy in accurately classifying 96.45% of the occurrences. With an NPV of 98.05%, the linear SVM demonstrated its accuracy in properly detecting 98.05% of cases predicted as negative. The suggested model, however, fared the best out of all of them, with the greatest NPV of 99.8%, demonstrating its remarkable accuracy in correctly recognising 99.8% of cases predicted as negative.

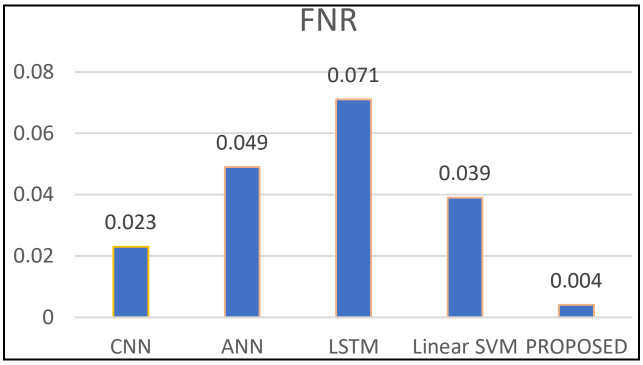
Figure 9 Comparison of the NPV metric (see online version for colours)



4.2.8 FNR

The FNR, a crucial indicator for evaluating a model's efficacy in detecting positive instances, becomes much more significant in situations when the loss of these instances is substantial. CNN showed a FNR of 2.3% in the ML model comparison, meaning that 2.3% of real positive occurrences were misclassified. With a 4.9% FNR, the ANN failed to detect real positive events in 4.9% of cases. The FNR of the LSTM model was 7.1%, meaning that the rate of misclassification for positive cases was 7.1%. With a 3.9% FNR, the linear SVM demonstrated a 3.9% inadequacy in detecting true positive cases. The suggested model notably fared better than all others, with the lowest FNR at 0.4%, highlighting its remarkable capacity to reduce the misclassification of real positive events as shown in Figure 10.

Figure 10 Comparison of the FNR metric (see online version for colours)

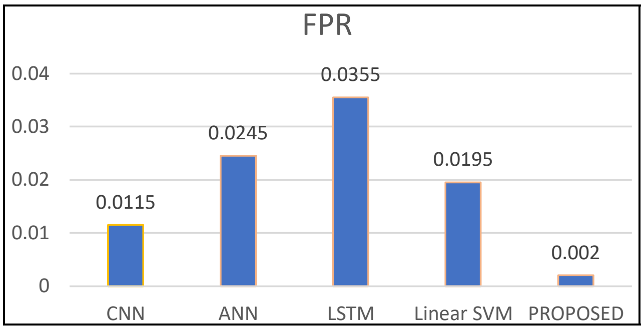


4.2.9 FPR

A crucial indicator for assessing a model's effectiveness is the FPR, which quantifies the percentage of true negative cases that are mistakenly classified as positive. CNN had an FPR of 1.15% in the ML model comparison, meaning that it misclassified real negative events at a rate of 1.15%. With an FPR of 2.45%, the ANN demonstrated a 2.45% misclassification rate for negative examples. The FPR of 3.55% for the LSTM model indicated a 3.55%

misclassification rate for real negative cases. An FPR of 1.95% was shown by the linear SVM, corresponding to a 1.95% misclassification rate for real negative cases. The suggested model performed remarkably better than all others, with the lowest FPR of 0.2%, highlighting its remarkable capacity to reduce the misclassification of real negative events as positives as shown in Figure 11.

Figure 11 Comparison of the FPR metric (see online version for colours)



Again we have compared our model with the model developed by Bandhu et al. (2022) who uses the stochastic gradient descent (SGD) and adaptive moment estimation (ADAM) optimiser and got the accuracies with 86% and 93%, but in our work we have used CNN and got overall 99.73% accuracy which indicates that our model performs better.

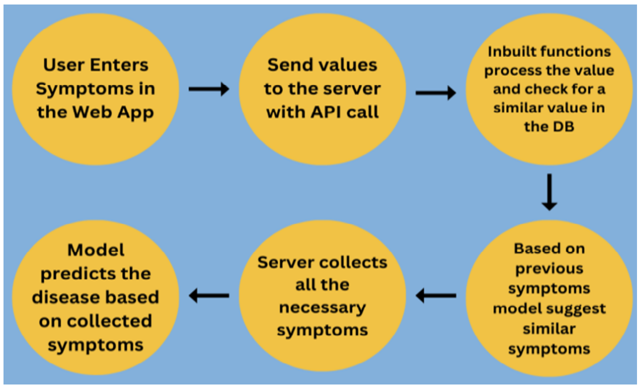
5 Web development for chatbot

The web application of the disease detection chatbot plays a crucial role in providing a user-friendly interface for patients to interact with the chatbot and obtain disease diagnoses based on their symptoms. It serves as a bridge between the advanced ML technology behind the disease detection model and the patients who can benefit from it. In our chatbot, patients can report symptoms or health concerns to the chatbot for preliminary assessments and recommendations. Then, the chatbot advises patients about the probable diseases and their precautions as an outcome. To implement the web application part of the disease detection chatbot, we followed the following steps:

First, we setup the Flask application by creating a new directory and initialising a virtual environment. Installing Flask using pip and creating a Python file, such as 'app.py', to define the Flask application, we imported necessary libraries like Flask, the trained disease detection model, and modules for processing user input and generating responses.

Next, we defined routes and views within the Flask application. We created a route for the home page ('/') where users can interact with the chatbot and defined a function to handle user requests and return appropriate responses. We utilised Flask's template engine (Jinja) to render HTML templates for the chatbot interface.

Figure 12 Flowchart for the web development for chatbot (see online version for colours)



Then we created HTML templates, such as 'home.html', for the home page in which we included an input field for users to enter their symptoms and setup a form submission mechanism to send the user input to the server.

We implemented the chatbot functionality by writing code to handle user input and generate responses. Then we used the trained disease detection model to process the symptoms provided by the user and retrieve the predicted disease and any additional information or recommendations. Then it formatted the response and sent it back to the user interface.

Then we tested the web application by running the Flask development server locally. We accessed the web application through a web browser and verified its functionality. We entered different symptoms and ensured that the chatbot accurately diagnoses diseases.

6 Conclusion and future work

In conclusion, the proposed methodology presents a holistic and advanced framework for the development of an efficient chatbot dedicated to providing immediate medical information to patients. The meticulous dataset collection and pre-processing set the stage for robust model training. The M-CNN, enriched with innovative components, demonstrates the model's capability to effectively learn and extract meaningful features from medical text data. The incorporation of the SA-MGO optimises the model's performance by fine-tuning key parameters. Integration into a user-friendly chatbot interface ensures accessibility, while ongoing evaluation and iterative fine-tuning based on user feedback contribute to continuous improvement. The proposed methodology, marked by its comprehensive approach and innovative components, positions the chatbot as a valuable and efficient resource for individuals seeking immediate insights into their health concerns prior to scheduled medical appointments.

Figure 13 Handling of requests (see online version for colours)

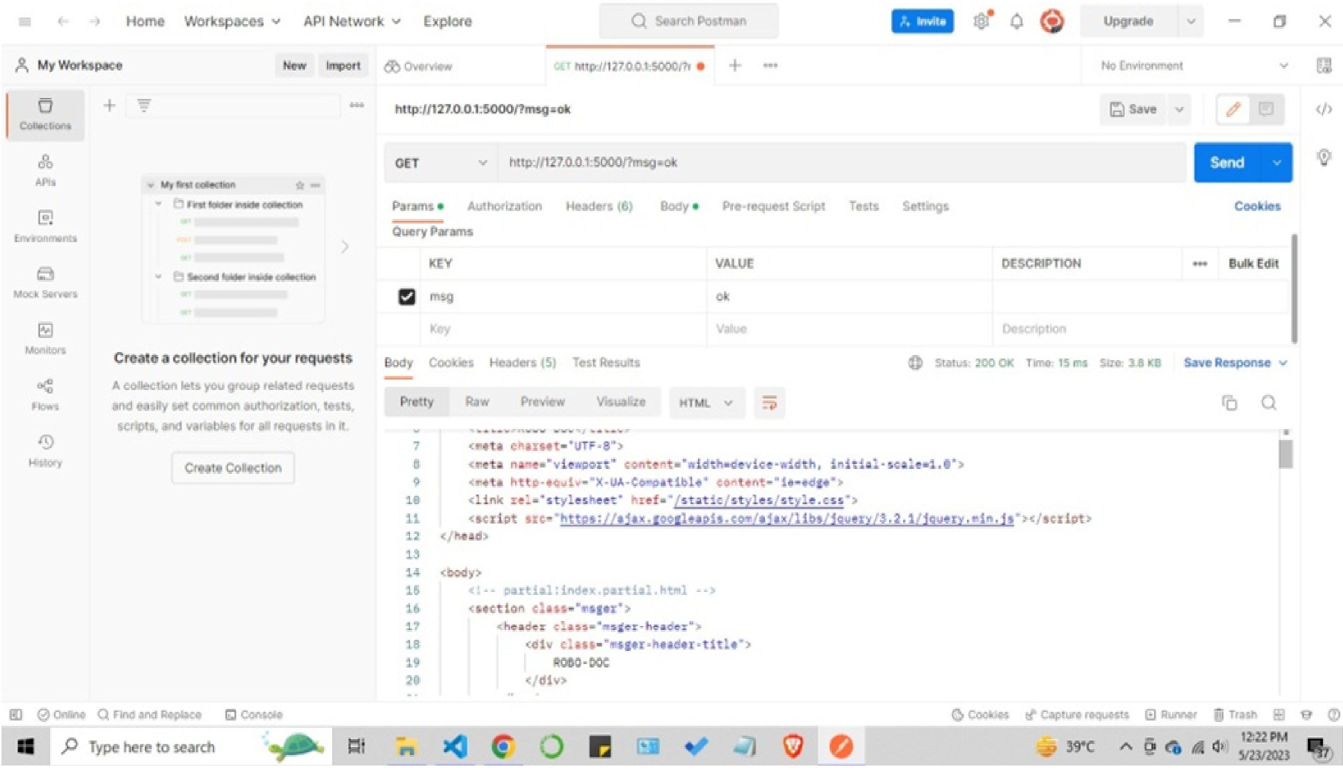


Figure 14 Initial phase of the chatbot (see online version for colours)

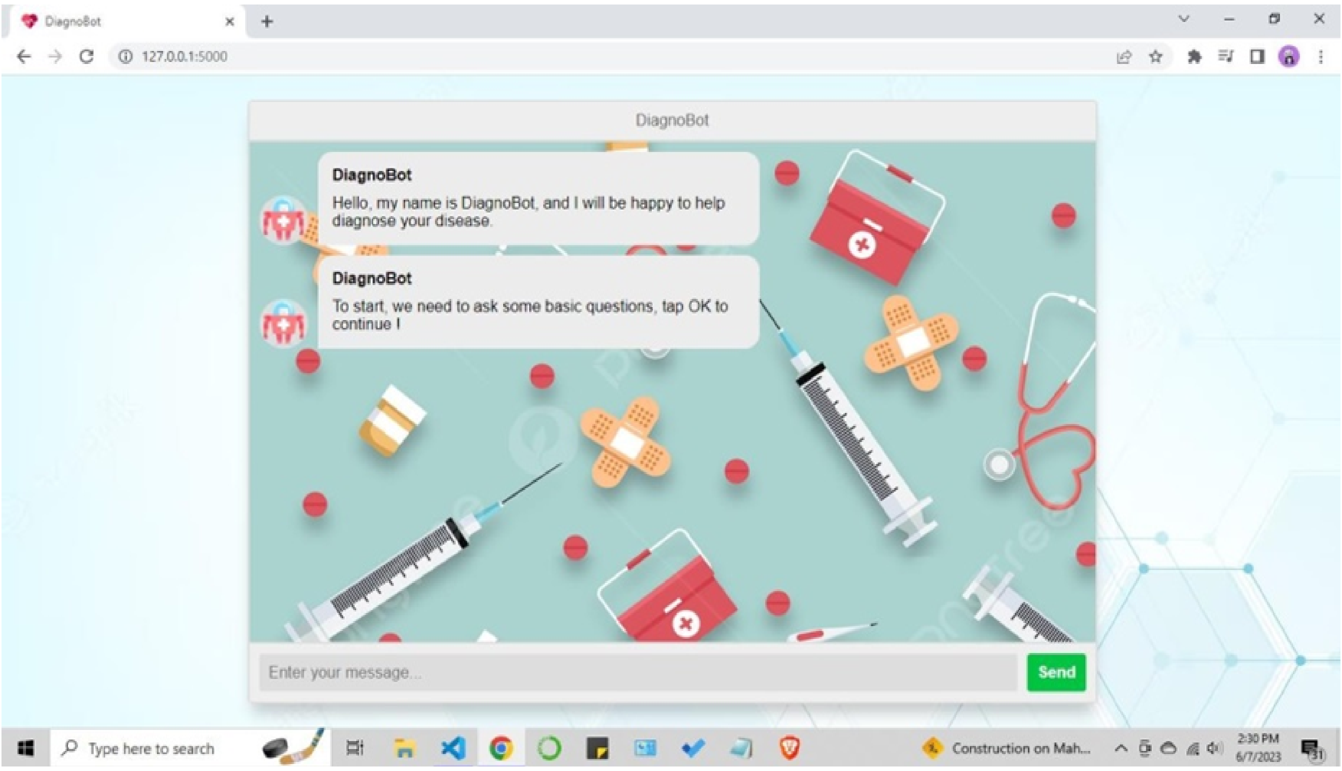


Figure 15 Interaction with the chatbot by the user (see online version for colours)

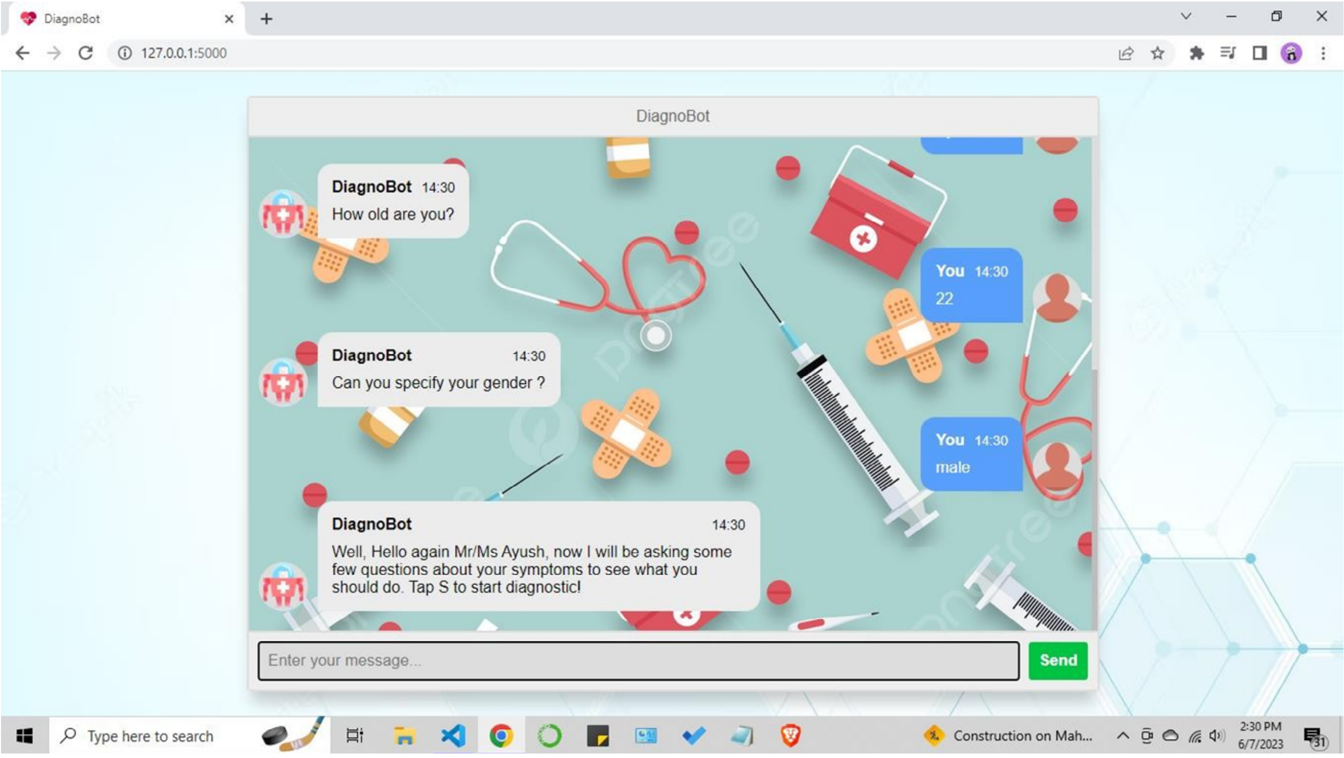


Figure 16 Prediction shown by the chatbot of dengue (see online version for colours)

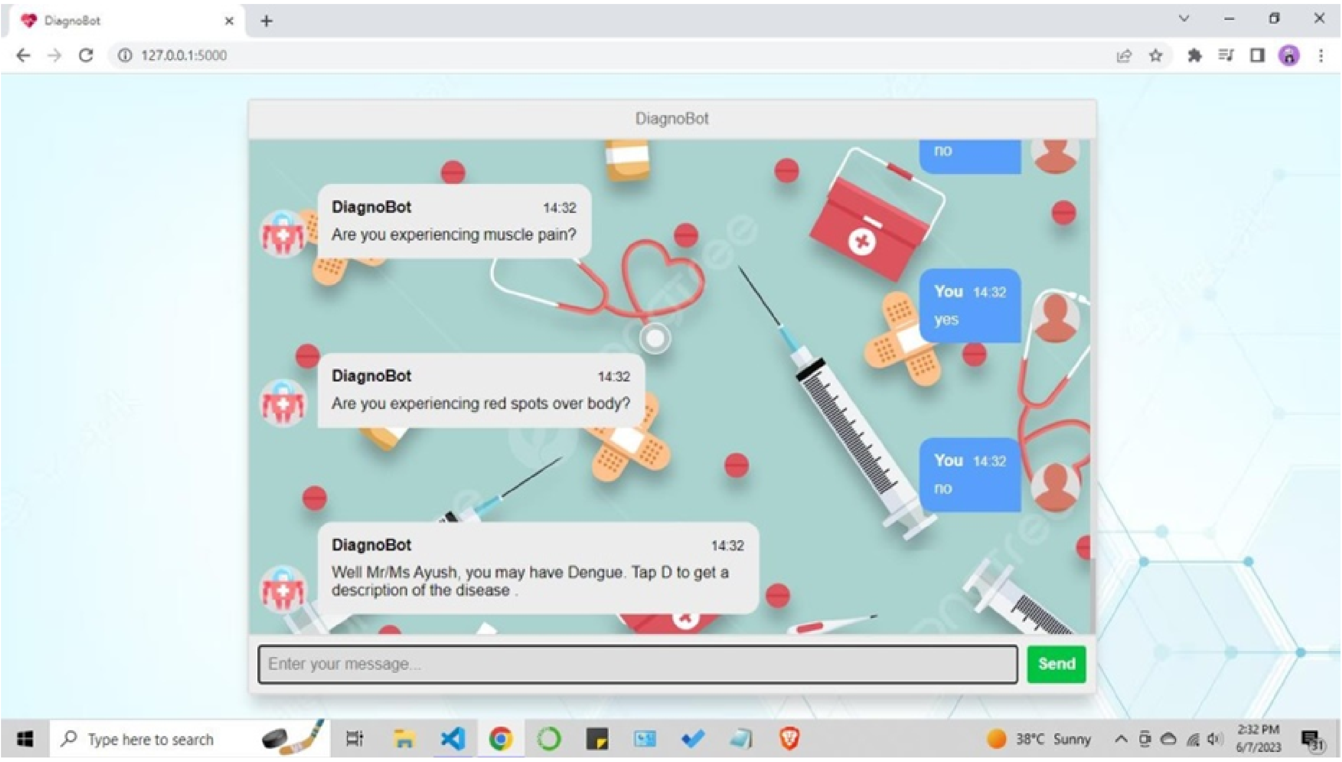


Figure 17 Chatbot showing description of the disease and precautions (see online version for colours)

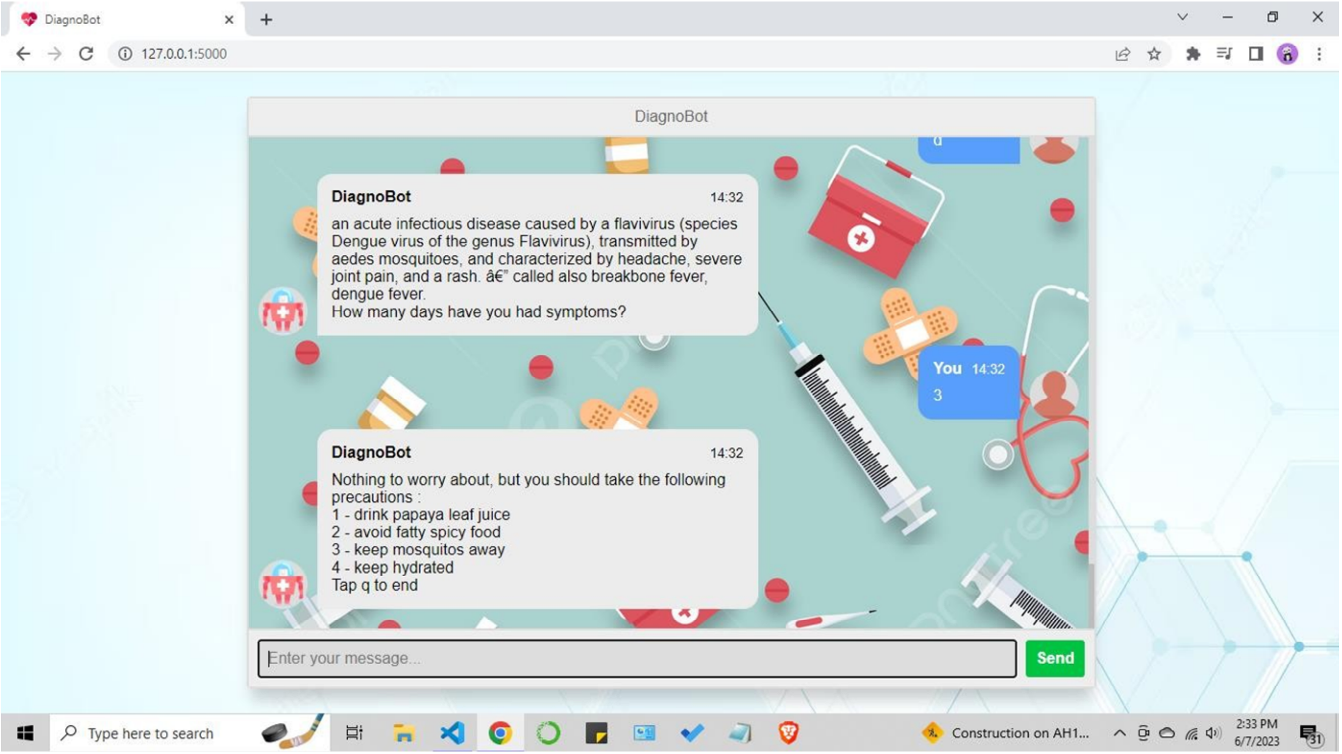


Figure 18 List of the diseases that chatbot detects (see online version for colours)

```
In [35]: set(disease)

Out[35]: {'(vertigo) Paroymsal  Positional Vertigo',
          'AIDS',
          'Acne',
          'Alcoholic hepatitis',
          'Allergy',
          'Arthritis',
          'Bronchial Asthma',
          'Cervical spondylosis',
          'Chicken pox',
          'Chronic cholestasis',
          'Common Cold',
          'Dengue',
          'Diabetes ',
          'Dimorphic hemmorhoids(piles)',
          'Drug Reaction',
          'Fungal infection',
          'GERD',
          'Gastroenteritis',
          'Heart attack',
          'Hepatitis B',
          'Hepatitis C',
          'Hepatitis D',
          'Hepatitis E',
          'Hypertension ',
          'Hyperthyroidism',
          'Hypoglycemia',
          'Hypothyroidism',
          'Impetigo',
          'Jaundice',
          'Malaria',
          'Migraine',
          'Osteoarthristis',
          'Paralysis (brain hemorrhage)',
          'Peptic ulcer diseae',
          'Pneumonia',
          'Psoriasis',
          'Tuberculosis',
          'Typhoid',
          'Urinary tract infection',
          'Varicose veins',
          'hepatitis A'}
```

There are some areas of the future research in medical like enhanced natural language understanding through which we could focus on improving the response more accurately and contextually. The other aspect of future work is validation and clinical trials which provide empirical evidence of its efficiency and safety in real world healthcare. Additionally, ongoing collaboration with IT teams and EHR vendors will be essential to maintaining seamless integration and promptly resolving any technical challenges that arise in our proposed model. In our work we have modified the CNN by using GA, GDN, FFT to conventional CNN, but this can be elaborated on time and computational complexity, particularly comparing GA, GDN, and FFT to conventional CNN.

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