Quality Festival 2025
ISBN 978-86-6335-121-9

Sandeep Kumar Mathariya[1]
Hemant Pathak
Priyanka Kumrawat
Digendra Singh
Mahaveer Jain
Hemang Shrivastava

Research paper,
DOI – 10.24874/QF.25.104

USE OF AN BGFT-DBI-LSTM AND PRFFC APPROACHES FOR ENHANCEMENT OF ONLINE DRUG RECOMMENDATION SYSTEM

Abstract: *For drug recommendations for all types of health issues, majority of the people have utilized online consultations in recent times. However, drugs' side effects differ from person to person. In existing research works, online drug recommendation systems according to people are not concentrated. Thus, this paper presents the Bayes Functional with Gaussian Tanh-based Deep Bidirectional Long Short-Term Memory (BFGT-DBi-LSTM)-based drug recommendation system. Initially, the tweets are gathered; by using Palma Ratio Farthest First Clustering (PRFFC), users are grouped according to their age. Next, from the user comment, the audio, video, and text are extracted. Primarily, the text data are pre-processed. By utilizing the WordNet effect and Sandiford Net, the emotion and score are labelled from the pre-processed data. Moreover, pre-processed data are inputted to the Bidirectional Encoder Representations from Transformers (BERT) word embedding. In the meantime, the features are extracted from the pre-processed data; by utilizing Congruence Coefficient-based AnasPlatyrhynchos Optimization (CC-APO), important features are chosen. Next, to predict drug safety, all the output is given as input to BFGT-DBi-LSTM. Subsequently, according to the output, the drug is recommended for the user. Conversely, the noise is removed from the audio data using Correlated Kalman Filter (CKF). After that, the audio is transformed into text and given for pre-processing. In addition, the audio is separated from the video and given as input to the noise-removal process of audio. Lastly, in experimental analysis, the proposed technique achieves superior outcomes.*

Keywords: *Online drug recommendation system; Congruence Coefficient based AnasPlatyrhynchos Optimization (CC-APO); Bidirectional Encoder Representations from Transformers (BERT;, Correlated Kalman Filter (CKF); Palma Ratio Farthest First Clustering (PRFFC); Natural Language Processing (NLP).*

1. Introduction

For handling the overloaded information of online users, the recommender system is an emerging field.

Generally, based on the user ratings and content presented in the user comments, the recommendation system is developed (Nistal-Nuño, 2022). For many research domains like tweets, documents, medicines, tweets related to different products, et cetera, the recommendation system is considered (Shahbazi and Byun, 2020). Particularly, to preserve human life from different medicinal products, healthcare-related tweets are very important (Sboev et al., 2022). As per some

[1] Corresponding author: Dr. Sandeep Kumar Mathariya
Email: mathariya@gmail.com

recent surveys, 55% of internet users gathered information about the health sector from the Mohapatra (2022). At the time of inaccessible time of doctors like pandemics, floods, et cetera, people access the online-centric health system (Posch & Tiwari, 2021). Moreover, for the diagnosis and treatment of diseases, people utilize a lot of medical consultation platforms (Yan et al., 2020). For providing suggestions to patients about diseases and illnesses, various countries are utilizing recommendation systems (Sharma et al., 2021). Hence, for preserving the patient's health, the drug recommendation system using online reviews is necessary. Mainly, to facilitate users' item selection process, the recommender system is integrated with online retailers, streaming services, and social networks (Mathariya & Srivastava, 2023). Generally, the recommendation system is developed using sentimental analysis scores like positive, negative, and neutral (Hossain et al., 2020). However, for the development of a sentiment analysis-based drug recommendation system, the manual decision-making process is difficult (Cui et al., 2023). Most of the researchers concentrate on automated recommendation systems (Ihnaini et al., 2021). Thus, for the recommendation system, various Machine Learning (ML) models like Support Vector Machine (SVM), Linear Discriminant Analysis (LDA), Probabilistic Neural Networks (PNN), Multi-Layer Perceptron (MLP), et cetera are utilized (Dara et al., 2022; Ochoa et al., 2021). Moreover, for the recommendation systems, different methods like neighbourhood collaborative filtering, content-based filtering, and so on are utilized (Tran et al., 2023). ML-based recommendation systems provide a higher quality recommendation than conventional recommender systems. However, some research problems, namely the availability of data, training time, higher error, and other problems are present in ML models (Blanco-Gonzalez et al., 2023). Therefore, a recommendation system is developed in this research approach by utilizing BFGT-DBi-LSTM.

A. *Problem statement*

Some research problems in existing research approaches are given below:

- Existing research works did not present a drug recommendation system according to the side effects of different age groups, which might affect the output of the drug recommendation system with respect to user reviews.
- In the existing paper (Bhimavarapu et al., 2022), the accuracy of the recommendation system depends on the threshold value, thus reducing the robustness of the recommendation system.
- In Haque et al. (2023), n-gram features were only utilized, which might affect the model's performance.
- Shiju and He (2022) were only based on the user's text comment, which caused an increase in the misclassification rate.
- In existing research works, expansion is utilized for abbreviation; however, the same abbreviation was presented in diverse areas, which might affect the model's performance.
- Existing research methodologies fail to cover the people's emotions during the analysis of the recommendation.

B. *Objectives*

Some research objectives presented to solve the existing research problems are,

- To present the drug recommendation according to the age group utilizing PRFFC.
- To present the automated system by utilizing the BFGT-DBi-LSTM technique.
- To include more features for the recommendation process.

- To consider the video, audio, and text-based comments.
- To include the expansion by considering keywords.
- To cover the people's emotions using the WordNet effect.

The research paper's structure is arranged as: section 2 describes the existing research works, section 3 explains the proposed drug recommendation system, section 4 describes the research's result analysis, and section 5 concludes the proposed research with future enhancement

2. Related work

Bhimavarapu et al. (2022) propounded a drug recommender system by utilizing a stacked Artificial Neural Network (ANN). The research considered that to reduce the side effects, the previous health profile of the patients was taken. In addition, it included the deep learning process for unbiased and fair drug recommendations. The experimental analysis examines the model's performance with the prevailing models. The model attained higher performance; however, the model's accuracy depended on the threshold variation of the parameter, thus affecting the robustness of the model.

Haque et al. (2023) aimed to enhance the sentiment analysis process for online drug reviews. Initially, the input was pre-processed; from the pre-processed data, the features were extracted. Next, to predict other users' drug recommendation process, the extracted features were inputted into five classifiers. The experimental analysis showed that the model attained 97.40% accuracy, which was higher than the prevailing research models. But it utilized only the n-gram feature, which might affect the model's performance.

Shiju and He (2022) established a multiple-supervised ML model to classify the user ratings of drugs. To classify the drug review rating, the research model used the Naïve Bayesian and Random Forest classifiers. The experimental assessment displayed that the model attained 87% accuracy, which was higher than the other models. However, it concentrated only on the text-centric comments from users; thus, it might increase the misclassification rate.

Sivakumar et al. (2023) suggested a random forest technique-based online drug recommendation system. Initially, the noises of the dataset were removed; next, the features of the dataset were given to the random forest classifier or obtaining the sentiment about the drug reviews. The performance analysis revealed that the model attained higher performance than the prevailing model. Nevertheless, the collected data samples had biases, which might affect the recommendation system's accuracy.

Rao et al. (2020) presented a medicine recommendation system cantered on patient reviews as well as performed sentiment analysis to choose the best medicine for diseases. To increase the recommendation system's performance, the research framework utilized the Light-gbm model. The presented model attained higher performance; but it failed to cover all the basic information about the medicine and patient, which might affect the model's performance.

Nair et al. (2024) introduced a drug recommendation classification system for a particular drug. Primarily, the data were gathered, and diverse language modelling were utilized in the collected data to obtain the embedding data using different embedding approaches, namely BERT, SciBERT, and Bio BERT. Moreover, different ML models were utilized for training the data. The classifier's performance was better than the prevailing classifiers. However, the obtained results were unreliable for a large amount of data.

Paliwal et al. (2022) presented a recommendation system cantered on sentiment analysis and radiant boosting. The polarity score analysed the sentiments, which were given as input to the Extreme

Gradient Boosting (XGBOOST) technique for recommendation classification. For the presented research, the mean average precision value was higher; however, the research's time complexity was high owing to the learning process's parameter.

Khattak et al. (2020) propounded the sentimental analysis integrated drug recommendation system. Here, public opinion was summarized, and the drug recommendation system was developed based on the summarization. The summarization process-centric recommendation attained a higher outcome than the other models. However, user information on the profile was not covered, which might affect the model's performance.

Basiri et al. (2020) established a recommendation system centered on two deep fusion models. The traditional learning algorithm was fused with one deep model in the first fusion model; the deep method's confidence score was used in the second fusion model. As per the results, the model results were improved by 4% than the traditional model. But, for all types of data, the confidence calculation wasn't similar; thus, it might affect the model's performance.

Han et al. (2020) developed a pre-training and multi-task learning model-centric drug recommendation system. For transferring the domain for helpful knowledge, the multi-task learning process was utilized. Moreover, it generated the dataset for review classification, and it consisted of one or more targets. According to the experimental outcomes, the model attained higher performance than the prevailing research models (Rani et al., 2024) But, there was a computational complexity issue in the presented learning model.

3. Proposed BGFT-DBI-LSTM based online drug recommendation system

This paper presents the online drug recommendation system on user reviews about drugs. Primarily, the user profiles are grouped under diverse age categories. Next, from each category, text, audio, and video comments are extracted. After that, further processes are carried out. Figure 1 shows the proposed research technique's block diagram.

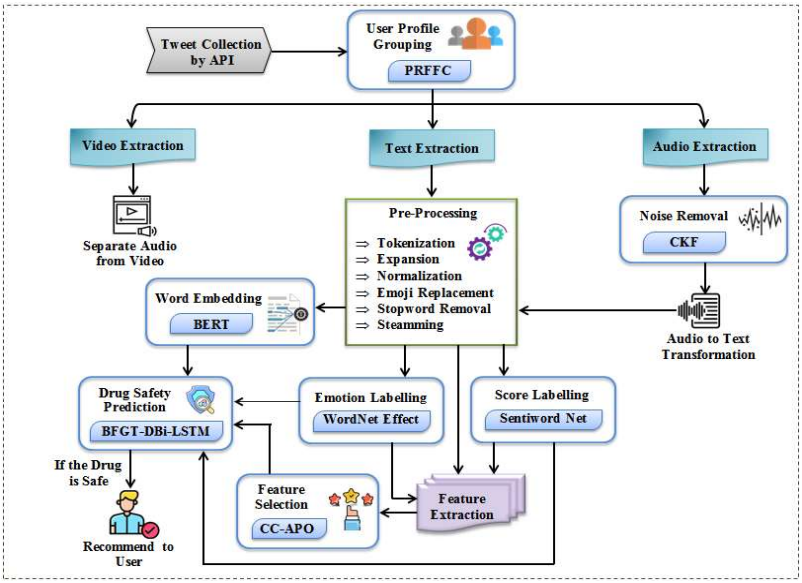


Figure 1. Block diagram for the proposed research methodology

Tweet Collection

Primarily, the Application Programming Interface (API) collects the tweets related to the drugs. The collected tweets T_{ts} are expressed as,

$$T_{ts} = \{T_1, T_2, T_3, ..., T_n\} \quad (1)$$

Here, T_n is the n-number of collected tweets.

User profile grouping

From the collected tweets T_{ts} , the user profiles are grouped according to their age since side effects vary according to the age category (Kalakoti et al., 2022). By using PRFFC, the user profile is grouped. The conventional FFC algorithm highly supports large amounts of data; however, the initial centroid point is selected randomly, which might create the cluster outlier problem (Nayak et al., 2023) Thus, to focus on the difference between the values of the whole input sample, this research approach utilizes the Palma ratio. From the Palma ratio value, a higher value is selected as the initial centroid, and further centroids are selected based on the first centroid. Initially, the initial centroid is chosen by utilizing the Palma ratio for the collected tweets T_{ts} .

$$w_1 = \frac{H(T_{ts})}{R(T_{ts})} \quad (2)$$

Where, w_1 is the initial centroid, $H(T_{ts})$ is the largest content of the tweet, and $R(T_{ts})$ is the remaining lowest content of the tweet. According to the initial centroid point, the furthest centroid points are selected according to their difference. The derived centroid points W_{cen} are expressed as,

$$W_{cen} = \{w_1, w_2, ..., w_n\} \quad (3)$$

Next, the distance between the derived centroids and the initial points is calculated using the Euclidean distance equation, which is given in equation (4),

$$\lambda_{dis} = \sqrt{\sum (T_{ts} - W_{cen})^2} \quad (4)$$

After that, similar distance-centric tweets are grouped. Then, it is checked whether all the input tweets are grouped or not. If it is grouped, then the iteration is terminated; or else, the iteration is increased. The checking condition CH_k is expressed in equation (5),

$$CH_k = \begin{cases} stop & if\ (T_{ts} == grouped) \\ I_z & else \end{cases} \quad (5)$$

The pseudocode for the PRFFC is displayed below,

Pseudocode for PRFFC

Input: Tweets $T_{ts} = \{T_1, T_2, T_3, ..., T_n\}$

Output: Cluster set $\wp_{cl} = \{\wp_1, \wp_2, ..., \wp_n\}$

Begin

Initialize centroid, and distance λ_{dis}

Calculate initial centroid by, $w_1 = \frac{H(T_{ts})}{R(T_{ts})}$

If distance==higher {

Select anothercentroid

} else {

Consider as data

} end if

For each T_{ts} do

$\lambda_{dis} = \sqrt{\sum (T_{ts} - W_{cen})^2}$

if $(T_{ts} == grouped)$ {

Stop

} else {

$$CH_k = I_z$$

} end if

End each

Return $\wp_{cl} = \{\wp_1, \wp_2, ..., \wp_n\}$

End

Clustered data is expressed as,

$$\wp_{cl} = \{\wp_1, \wp_2, ..., \wp_n\} \quad (6)$$

Here, I_z signifies the increase in the iteration count, $\wp_{cl}$ depicts the cluster set, and $\wp_n$ indicates the n-number of clusters.

C. Text extraction

Here, the texts are extracted from the clustered output $\wp_{cl}$ based on the age of the people. Drug safety is predicted from the extracted text tweet, followed by pre-processing, emotion labelling, score labelling, feature extraction, and feature selection process.

a) Pre-processing

Here, to improve the accuracy of the drug safety prediction process, the initial input texts κ_{tx} are pre-processed. Initially, the abbreviated terms of κ_{tx} are expanded by a smart expansion tool, including keywords related to the working environment. P. Chinnasamy (2023) Next, tokenization is carried out, thus splitting the text into a set of tokens. Subsequently, each token is normalized (i.e., all the letters are changed into the same order either a small letter or a capital letter). After that, the words replace the emojis in the tokens, and the stop words are removed. Next, to avoid the prefixes and suffixes of the initial text data, the stemming process is performed for the input data. Mathematically, the pre-processed data is given as,

$$\text{▯}_{st} = \{\text{▯}_1, \text{▯}_2, ..., \text{▯}_n\} \quad (7)$$

Where, ▯_{st} is the pre-processed data set and ▯_n is the n-number of pre-processed data.

b) Emotion labelling

For considering the patient's emotions while using the specific drugs, the emotion is labelled from the pre-processed data by utilizing the WordNet effect. It consists of more number of emotions with their meanings. The emotion labelled output is signified as E_l.

$$E_l = \{Ti_c, \text{▯}_{st}\} \quad (8)$$

Here, Ti_c depicts the emoticons for specific pre-processed data.

c) Score labelling

In this, for analyzing the sentiment of user comments about the drug, the score is labelled from the pre-processed data for each word. The score labelling is the combination of positive p_v, negative n_v, and neutral n_l, which is mathematically derived as,

$$S_l = \{p_v, n_v, n_l\} \quad (9)$$

Where, S_l is the score labelled output.

d) Feature extraction

Here, to improve the drug safety prediction process, features are extracted from ▯_{st}. Here, Term Frequency (TF), TF-IDF, Inverse Document Frequency (IDF), relevant noun identification, uni-grams, bi-grams, N-gram features, et cetera are extracted. The

extracted features φ_f are specified in equation (10),

$$\varphi_f = \{\varphi_1, \varphi_2, ..., \varphi_n\} \quad (10)$$

Here, φ_n is the n-number of extracted features.

e) Feature selection

Here, to reduce the computational complexity time of the drug safety prediction process, the important features are selected from the extracted features by using the CC-APO algorithm. The Anas platyrhynchos has better-controlling parts; thus, it produces a better local optimal solution. However, the iteration count is centered on the coefficient, which might provide a poor convergence. For solving this problem, this research methodology utilizes the Congruence coefficient, which investigates the similarity between the populations. The algorithm chooses the population centered on their two main behaviours, namely warning behaviour and moving process. Initially, the extracted features are regarded as the Anas platyrhynchos. The population position is initialized centered on equation (11),

$$a = a_{low} + \Re.\left(a_{high} - a_{low}\right) \quad (11)$$

Where, a is the initialized population, a_{low} and a_{high} are the lower and upper bound of the search space of the population, and $\Re$ signifies the random number. Next, the fitness function ψ_f is estimated for the initialized population position using equation (12),

$$\psi_f = \max(\text{ac}) \quad (12)$$

Where, the maximum accuracy value $\max(\text{ac})$ of drug safety prediction is considered as the fitness function. After that, the position updation centered on the warning behaviour is carried out. The warningbehaviour-based updation process regarding the probability of distress ρ_{dis} calculation is given as,

$$\rho_{dis} = \frac{\tau_k\left(a\left(\psi_f\right)\right)}{N} \quad (13)$$

Here, $\tau_k\left(a\left(\psi_f\right)\right)$ is the rank of the individual fitness population, and N is the number of population. If ρ_{dis} is satisfied, then the position of the population is updated using equation (14),

$$a(\varepsilon+1) = a(\varepsilon) + \sigma(\Re - 0.5) \times v_0 \times \left|a(\varepsilon) - a_{bt}(\varepsilon)\right| \times \upsilon_y(j) \quad (14)$$

Where, ε depicts the current iteration, σ signifies the sign function, $a_{bt}(\varepsilon)$ is the best population, and v_0 specifies the step length scale factor. Levy distribution $\upsilon_y(j)$ and its step length j is derived in equation (15) and (16),

$$\upsilon_y(j) \sim \varpi = r^{-\varsigma} \quad (15)$$

$$j = \frac{\varpi}{|v|^{\frac{1}{\beta}}} \quad (16)$$

Here, β, ϖ, and v are the parameters of the uniform distribution function, and r is the iteration parameter of the levy distribution function.

Subsequently, the population updation procedure is carried out according to the moving process. The mathematical formulation of the moving process is derived using (17),

$$a(\varepsilon+1) = a(\varepsilon) - Z\left|H \times a_{bt}(\varepsilon) - a(\varepsilon)\right| \quad (17)$$

Here, Z and H are the coefficient vectors. Here, the coefficient vectors are derived by

utilizing the congruence coefficient function, which is expressed in equation (18),

$$Z = 2i \times \left(\frac{\sum a.a(\varepsilon+1)}{\sqrt{\sum a^2 \sum (a(\varepsilon+1))^2}} \right) \times \Re - i \quad (18)$$

$$H = 2\Re \times \left(\frac{\sum a.a(\varepsilon+1)}{\sqrt{\sum a^2 \sum (a(\varepsilon+1))^2}} \right) \quad (19)$$

Here, $\Re$ is the coefficient vector, which linearly decreases with the iterations, and it is expressed as,

$$\Re = 2 - \varepsilon \frac{2}{\max(\varepsilon)} \quad (20)$$

The maximum number of iterations is indicated as $\max(\varepsilon)$. If the derived updation of the moving process is worse, then another random particle a_{rd} is selected. If the selected a_{rd} is better than a, then the individual particle moves to the further updation process, which is derived in equation (21),

$$a(\varepsilon+1) = (a_{rd}(\varepsilon) - a(\varepsilon)) \times e^{-h^2} + a(\varepsilon) \quad (21)$$

Here, h is the distance of the random particle. If a_{rd} is equal to a, then the population is unchanged. If a_{rd} is worse than a, then further updation process is derived in equation (22),

$$a_{rd}(\varepsilon+1) = (a(\varepsilon) - a_{bt}(\varepsilon)) \times e^{-h^2} + a_{rd}(\varepsilon) \quad (22)$$

CC-APO's pseudocode is given as follows:

Pseudocode for CC-APO

Input: Extracted features $\varphi_f = \{\varphi_1, \varphi_2, ..., \varphi_n\}$

Output: Selected features $\delta_{sf} = \{\delta_1, \delta_2, ..., \delta_n\}$

Begin

Initialize population, iteration ε and maximum iteration $\max(\varepsilon)$

Compute fitness ψ_f

Set iteration $\varepsilon = 1$

While $(\varepsilon \le \max(\varepsilon))$ do

Updatethe position of the population

Warning behaviour

Calculate probability of distress ρ_{dis}

If $\rho_{dis} == satisfied$ {

Updation by $a(\varepsilon+1) = a(\varepsilon) + \sigma(\Re - 0.5) \times v_0 \times |a(\varepsilon) - a_{bt}(\varepsilon)| \times \upsilon_y(j)$

} else {

Followed the previous position

} end if

#Moving behaviour

Update population position by

$$a(\varepsilon+1) = a(\varepsilon) - Z|H \times a_{bt}(\varepsilon) - a(\varepsilon)|$$

Calculate fitness

Set iteration $\varepsilon = \varepsilon + 1$

End while

Return δ_{sf}

End

The selected features are expressed as,

$$\delta_{sf} = \{\delta_1, \delta_2, ..., \delta_n\} \quad (23)$$

Here, φ_n is the n-number of extracted features.

f. Word embedding

Here, to obtain more information for the input text comments, the polarity value is found out for $\square_{st}$. The BERT approach supports large amounts of data. The BERT is trained based on 2 tasks, namely masked language tasks and unmasked language tasks. Embedding and self-attention mechanisms are carried out for both tasks. By utilizing the embedded matrix, the tokens TK_s of $\square_{st}$ are initially converted into the embedded vector, and it is mathematically derived in equation (24),

$$E_v = X_{E_v}\left(TK_s\right) \tag{24}$$

Here, E_v is the embedded vector and X_{E_v} is the embedded matrix. Next, the self-attention mechanism is calculated for each token by using equation (25),

$$TT_u = \chi\left(\frac{Y\gamma_y^{\Im}}{\sqrt{m_e}}\right) \tag{25}$$

Where, $\Im$ is the transpose function, χ is the softmax activation, Y is the query, and γ_y signifies the key, and dimension is indicated as m_e. The softmax activation function is given in equation (26),

$$\chi = \frac{e^{TT_u}}{\Sigma e^{TT_u}} \tag{26}$$

Finally, the polarity value of the $\square_{st}$ is indicated as ς_p.

D. Drug Safety Prediction

Here, to predict the safety of the drug, ς_p, δ_{sf}, S_l, and E_l are given as input to the BFGT-DBi-LSTM. Conventional DBi-LSTM has a sequence padding function; thus, all the inputs are initially ordered. However, due to the ineffective hyperparameter and vanishing gradient problem, it has computational problems. Thus, to reduce the vanishing gradient problem, this research methodology utilizes the Bayes function for the hyperparameter selection and Gaussian Tanh activation instead of the conventional Tanh function. Figure 2 displays the structure of the BFGT-DBi-LSTM,

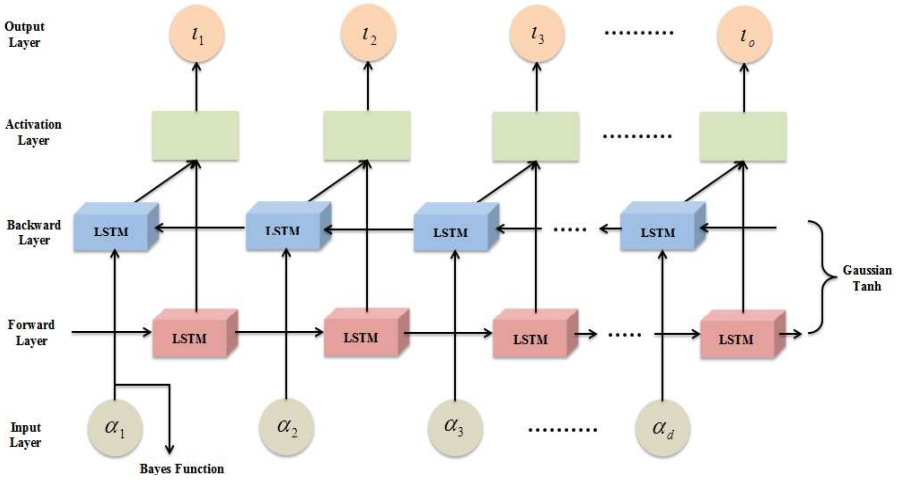


Figure 2. Structure of the BFGT-DBi-LSTM algorithm

The BiLSTM has a forward layer, input layer, backward layer, activation layer, and output layer. The input data α_d is indicated as,

$$\alpha_d = \left\{ \varsigma_p, \delta_{sf}, S_l, E_l \right\} \tag{27}$$

Initially, the Bayes function is derived for the hyperparameter tuning process L_m, which is given as,

$$L_m = \frac{L(O_n).L(O_{n+1}|O_n)}{L(O_{n+1})} \tag{28}$$

Here, O_n and O_{n+1} are the hyperparameters. The forget gate is presented in the forward layer and backward layer. Primarily, the forget gate is initiated. It is a combination of the previous outputs, and it determines how much information is preserved from the previous iteration. The derivation of the forget gate $\aleph_f$ is expressed in equation (29),

$$\aleph_f = \text{▯}\left(\text{▯}_{fw} \left[\iota_{o-1} \right], \alpha_d, \text{▯}_{fb} \right) \tag{29}$$

Here, ▯_{fw} and ▯_{fb} specify the weight value and bias values of the forget layer, correspondingly, ▯ is the activation function, and ι_{o-1} is the output of the previous iteration. Next, the input gate operation is performed, and it decides which information to store in the memory cell. The mathematical formulation of the input gate $\aleph_i$ is expressed as,

$$\aleph_i = \text{▯}\left(\text{▯}_{iw} \left[\iota_{o-1} \right], \alpha_d, \text{▯}_{ib} \right) \tag{30}$$

Where, ▯_{iw} and ▯_{ib} are the weight and bias values of the input gate, correspondingly. After that, Gaussian Tanh activation $\aleph_{gt}$ is derived to learn the large sequence data, which is given as,

$$\aleph_{gt} = \left(\alpha_d .0.5 \left[1 + e^{\left(\frac{\alpha_d}{2} \right)} \right] \right) * \left(\text{▯}\left(\text{▯}_{tw} \left[\iota_{o-1} \right], \alpha_d, \text{▯}_{tb} \right) \right) \tag{31}$$

Lastly, the output gate $\aleph_o$ operation is done. It is responsible for deciding which information is utilized for the output process, and the derivation is exhibited in equation (32),

$$\aleph_o = \text{▯}\left(\text{▯}_{ow} \left[\iota_{o-1} \right], \alpha_d, \text{▯}_{ob} \right) \tag{32}$$

$$\iota_{o-1} = \aleph_o * \aleph_{gt} \tag{33}$$

The output layer's weight and bias values are signified as ▯_{ow} and ▯_{ob}, correspondingly. BiLSTM first passes the input to the layer in sequence order (i.e., forward layer). Then, the reverse form of the input sequence is fed into the BiLSTM (i.e., backward layer). Hence, the process of deep learning is followed by the learning process. The BFGT-DBi-LSTM's output gives the safety and non-safety of the specific drugs.

E. Audio extraction

Here, the audio data is also extracted from $\wp_{cl}$. Next, to enhance the quality of the audio, the noises of the audio are removed using CKF. Conventional KF has a high ability to reduce noise in the signal. But, it minimizes the noise centered on the relationship between the frequency ranges of the signal and does not consider the strength between the ranges. Primarily, the system state and the error covariance for the input audio signal DI_o are estimated.

$$EM_{st} = Rt.EM_2 \tag{34}$$

$$E_{\text{cov}} = Rt.E_{\text{cov}_2}.Rt^T \tag{35}$$

$$E_{cor} = \frac{\sum \left(cr_i - \overline{cr_i}\right)\left(cr_{i+1} - \overline{cr_{i+1}}\right)}{\sqrt{\sum \left(cr_i - \overline{cr_i}\right)^2 \sum \left(cr_{i+1} - \overline{cr_{i+1}}\right)^2}} \quad (36)$$

Where, EM_{st} is the state variable of the signal, E_{cov} is the state covariance matrix, Rt is the state transition matrix, E_{cor} is the state correlation matrix, cr_i is samples from tweets, and $\overline{cr_i}$ is the mean samples of the tweets. Next, Kalman gain is estimated. The state variable, covariance variable, and correlation variable are again calculated based on the Kalman gain, which removes the noise from the signal. Noise removed signal is indicated as NR_s. From NR_s, the audio is transformed into text. Subsequently, the process of text data is also utilized for text data extracted from audio, which is described in sections 3.3 and 3.4.

F. Video Extraction

Here, video data is extracted from $\wp_{cl}$. The audio from the video is separated and given to the noise removal process, and further steps of the audio extraction process are performed, which is described in section 3.5. Lastly, the medicine is recommended to the user based on the predicted outcome.

4. Result and discussion

Here, the proposed research approach's performance is investigated, and the proposed research is implemented in the working platform of Python.

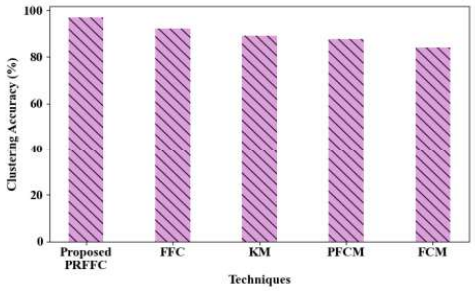
A. Dataset Description

In this research approach, the symptom disease dataset that is publically available is utilized for the performance analysis, and the resource link is mentioned under the reference section. The dataset contains the symptoms of the medicine shown by the patients. From the dataset, 80% and 20% of the data are utilized for training and testing purposes, respectively.

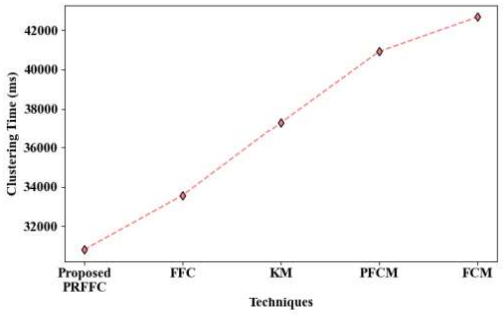
B. Performance analysis

(a) Performance analysis of clustering

Here, the proposed PRFFC's performance is compared with the existing Farthest First Clustering (FFC), K-Means (KM), Probabilistic Fuzzy C-Means (PFCM), and Fuzzy C-Means (FCM) algorithms.



(a)



(b)

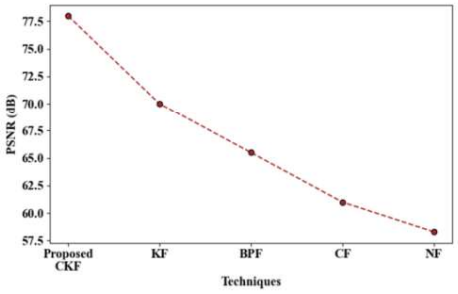
Figure 3. Performance analysis regarding (a) clustering accuracy and (b) clustering time

Figure 3 displays the clustering accuracy and clustering time of the clustering process. Based on the Palma ratio, the proposed clustering approach selects the initial centroid; thus, it has higher accuracy (96.6%) and lower training time (30829ms). The approach is denoted as the best approach if it takes less time and has higher accuracy. Here, the existing clustering approach's average accuracy is 88.22, and the average training time of the existing approach is 38615.25ms, which is higher than the

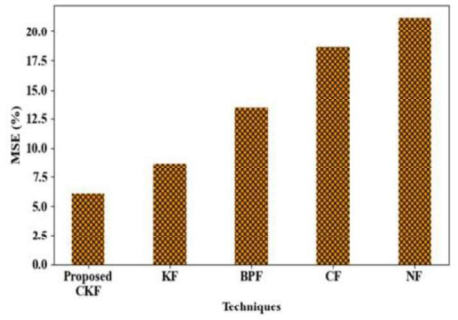
proposed model. Hence, it denotes that the approach is highly helpful for the clustering process of the user profile.

(b) Performance analysis of noise removal

The proposed CKF's performance is analyzed with the prevailing Kalman Filter (KF), Band Pass Filter (BPF), Chebyshev Filter (CF), and Notch Filter (NF) regarding Peak Signal Noise Ratio (PSNR) and Mean Squared Error (MSE).



(a)



(b)

Figure 4. Graphical representation of noise removal process (a) PSNR and (b) MSE

In Figure 4, the performance of the noise removal methodologies regarding the PSNR and MSE metrics is represented. Here, the proposed CKF approach's PSNR value is 78dB and the MSE is 6.1%. The proposed achieves a higher PSNR value and lower MSE than existing research methodologies. This is because the proposed approach considers the strength of the frequency range also. Here, the NF attains a very low PSNR (58.3dB) and higher MSE (21.2%) than the proposed and other existing research approaches. Hence, it displays that the model is highly suitable for noise reduction of the audio signal.

(c) Performance analysis of feature selection

Here, the proposed CC-APO approach's performance is compared with the existing APO, Coati Optimization (CO), Lyre Bird Optimization (LBO), and Egret Swarm Optimization (ESO) algorithms.

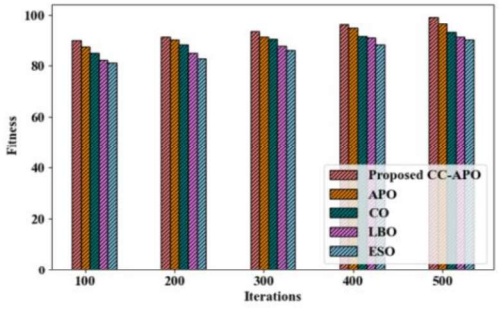


Figure 5. Fitness vs iteration analysis

Figure 5 displays the fitness Vs iteration analysis. This research methodology considers the maximization accuracy of the classifier as the fitness function. When the iteration count is 200, the proposed CC-APO attains 91.1% fitness, which is higher than the existing research methods. This is because the congruence coefficient process solves the poor convergence problem. For the same iteration count, the existing research approaches achieved a lesser fitness function than the proposed model.

(d) Performance analysis of classification

Here, the proposed BFGT-DBi-LSTM's performance is analyzed with the Recurrent Neural Network (RNN), BiLSTM, Convolutional Neural Network (CNN), and ANN.

In Table 1, the statistical metric-based performance analysis of the classifiers, namely precision, accuracy, recall, False Positive Rate (FPR), F-Measure, False Negative Rate (FNR), and Mathew's Correlation Coefficient (MCC) is displayed.

Table 1. Statistical Metric-Based Performance Analysis Of The Classifiers

Metrics	Proposed BFGT-DBi-LSTM	BiLSTM	RNN	CNN	ANN
Accuracy	98.9	97.6	95	93.2	90
Precision	97	95	94.2	91.5	89
Recall	97.5	95.2	94	91	90
F-measure	97.2	95.1	94.1	91.2	89.5
FNR	0.0463	0.0671	0.0892	0.1298	0.1561
FPR	0.0561	0.0786	0.0908	0.1290	0.1498
MCC	98.2	95	93.7	91.6	87

The proposed BFGT-DBi-LSTM's accuracy is 98.9, which is higher than the existing approaches. This is because the hyper-parameter tuning and vanishing gradient problems are solved by the Bayes function and the Gauss Tanh activation function. Based on the other metrics also, the proposed methodology achieves higher performance than the existing methods. The accuracy value of the existing classifiers is 97.6% for Bi-LSTM, 95% for RNN, 93.2% for CNN, and 90% for ANN. Therefore, the analysis exhibits that the model is highly suitable for the drug safety prediction process.

Figure 6 shows the proposed and existing classifiers' Area Under Curve (AUC) analysis. An aggregate measure of performance across all possible classification thresholds is provided by the AUC.

For the proposed BFGT-DBi-LSTM, the AUC value (0.98) is higher. However, because of vanishing gradient and hyper-parameter tuning problems, the existing research methodologies have a lesser AUC value than the proposed model.

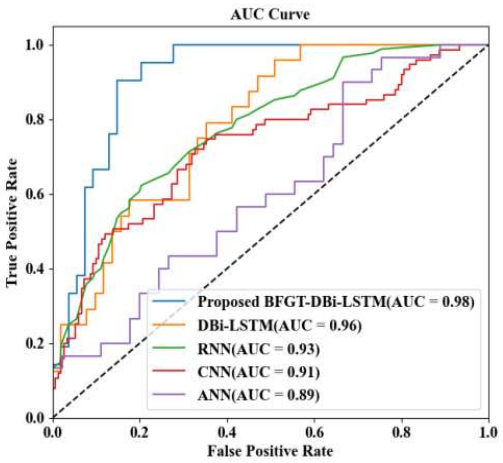


Figure 6. AUC analysis

Table 2. Error Analysis

Metrics	Proposed BFGT-DBi-LSTM	BiLSTM	RNN	CNN	ANN
MSE	1.9	5.6	9.2	12.5	16
MAE	2.3	5.8	10.3	13.8	18.2
RMSE	0.6	5.8	8.2	12.6	15

In Table 2, the error analysis of the classifiers with the existing classifiers regarding the Mean Absolute Error (MAE), Mean Square Error (MSE), and Root Mean Square Error (RMSE) is displayed. Here, the proposed technique has lower MSE (1.9), MAE (2.3), and RMSE (0.6); however, the prevailing classifiers have higher MSE, MAE, and RMSE values. Among existing classifiers, the ANN provides a much lower performance than the other prevailing research techniques. As per the analysis, the proposed system is highly helpful for the drug recommendation system.

The graphical representation of the training time analysis of the drug safety prediction process by different classifiers is presented in Figure 7.

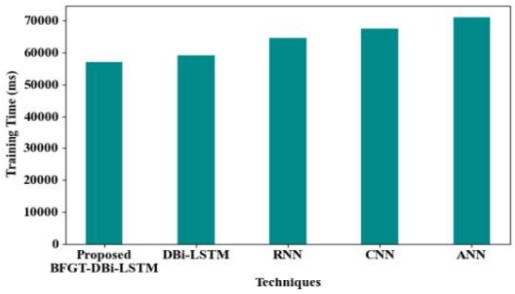


Figure 7. Training time analysis

The time difference between the starting time and ending time of the classifiers is defined as the training time. Here, the classifier's training time is 56932ms, which is lower than the prevailing classifiers. To train the data, the existing algorithm takes more time. The existing classifier's average training time is 65433.75ms. The enhancement of the proposed technique-centric drug recommendation system is also proved by the training time analysis.

C. Comparative analysis

Here, the proposed drug recommendation system's performance is assessed with the prevailing research works.

In Table 3, the comparative analysis of the proposed work with the prevailing research works centered on accuracy as well as RMSE metrics is displayed. Since the proposed model considers a clustering approach for tweet user grouping, the score labelling, and emotion labelling process, it attains higher accuracy (98.9%) with lower error (0.6 RMSE).

Table 3. Comparative Analysis Of The State-Of-Art Works

Author's Name	Methods	Accuracy	RMSE
Vianny et al., 2023	Particle Swarm Optimization (PSO)-Artificial Neural Network (ANN)	-	0.1040
Rani et al., 2024	LSTM	94%	-
Kalakoti et al., 2022	Deep Neural Network	0.79	-
Nayak et al., 2023	ML model	89.93%	-
Chinnasamy et al., 2023	Restricted Boltzmann Machine (RBM)-Coevolutionary Neural Network (CNN)	94.71%	2.72
Proposed	BFGT-DBi-LSTM	98.9	0.6

When compared to other prevailing research works, (Kalakoti et al., 2022) has a much lower accuracy (0.79). The superiority of the proposed research work over the existing research models is exhibited in the overall analysis.

5. Conclusion

This paper presented the BFGT-DBi-LSTM approach-based drug recommendation system. The proposed research's significant phases are user profile grouping, emotion labelling, score labelling, feature extraction, feature selection, and drug safety prediction. The drugs are recommended to the users according to the predicted output of drug safety. The experimental analysis investigates the proposed research technique's performance with the prevailing research approaches. This research methodology utilizes the publically available dataset for the performance analysis. The proposed classifier attains higher accuracy

with lower training time and RMSE than the prevailing classifiers and conventional works. 98.9%, 56932ms, and 0.6 are the accuracy, training time, and RMSE of the BFGT-DBi-LSTM, respectively. When analogized to conventional techniques, the remaining proposed methodologies also attained higher performance. Thus, the analysis shows that for drug recommendation systems, the proposed system is highly helpful in preserving patient health. But, for the recommendation process, the research considers less number of medicines.

Future scope: The proposed methodology can be enhanced in the future by including more medicines-based recommendation systems with advanced approaches for improving the system performance.

Acknowledgement: Acknowledgments of people, grants, funds, etc. should be placed in a separate section before the reference list. The names of funding organizations should be written in full (optional). Do not include author biographies.

References:

Basiri, M. E., Abdar, M., Cifci, M. A., Nemati, S., & Acharya, U. R. (2020). A novel method for sentiment classification of drug reviews using fusion of deep and machine learning techniques. Knowledge-Based Systems, 198, 105949. doi: 10.1016/j.knosys.2020.105949.

Bhimavarapu, U., Chintalapudi, N., & Battineni, G. (2022). A fair and safe usage drug recommendation system in medical emergencies by a stacked ANN. *Algorithms*, *15*(6), 186. doi: 10.3390/a15060186.

Blanco-Gonzalez, A., Cabezon, A., Seco-Gonzalez, A., Conde-Torres, D., Antelo-Riveiro, P., Pineiro, A., & Garcia-Fandino, R. (2023). The role of AI in drug discovery: challenges, opportunities, and strategies. *Pharmaceuticals*, *16*(6), 891. doi: 10.3390/ph16060891.

Chinnasamy, P., Wong, W. K., Raja, A. A., Khalaf, O. I., Kiran, A., & Babu, J. C. (2023). Health Recommendation System using Deep Learning-based Collaborative Filtering. *Heliyon*, *9*(12), e22844. doi: 10.1016/j.heliyon.2023.e22844.

Cui, J., Wang, Z., Ho, S. B., & Cambria, E. (2023). Survey on sentiment analysis: evolution of research methods and topics. *Artificial Intelligence Review*, *56*(8), 8469-8510. doi: 10.1007/s10462-022-10386-z.

Dara, S., Dhamercherla, S., Jadav, S. S., Babu, C. M., & Ahsan, M. J. (2022). Machine learning in drug discovery: a review. *Artificial intelligence review*, *55*(3), 1947-1999. doi: 10.1007/s10462-021-10058-4.

Dataset:https://huggingface.co/datasets/duxprajapati/symptom-disease-dataset/viewer/default/train

Han, Y., Liu, M., & Jing, W. (2020). Aspect-level drug reviews sentiment analysis based on double BiGRU and knowledge transfer. *IEEE Access*, *8*, 21314-21325. doi: 10.1109/ACCESS.2020.2969473.

Haque, R., Laskar, S. H., Khushbu, K. G., Hasan, M. J., & Uddin, J. (2023). Data-driven solution to identify sentiments from online drug reviews. *Computers*, *12*(4), 87. doi: 10.3390/computers12040087.

Hossain, M. D., Azam, M. S., Ali, M. J., & Sabit, H. (2020, December). Drugs rating generation and recommendation from sentiment analysis of drug reviews using machine learning. In *2020 Emerging Technology in Computing, Communication and Electronics (ETCCE)* (pp. 1-6). IEEE. doi: 10.1109/ETCCE51779.2020.9350868.

Ihnaini, B., Khan, M. A., Khan, T. A., Abbas, S., Daoud, M. S., Ahmad, M., & Khan, M. A. (2021). A smart healthcare recommendation system for multidisciplinary diabetes patients with data fusion based on deep ensemble learning. *Computational Intelligence and Neuroscience*, *2021*(1), 4243700. doi: 10.1155/2021/4243700.

Kalakoti, Y., Yadav, S., & Sundar, D. (2022). Deep neural network-assisted drug recommendation systems for identifying potential drug–target interactions. *ACS omega*, *7*(14), 12138-12146. doi: 10.1021/acsomega.2c00424.

Khattak, A. M., Batool, R., Satti, F. A., Hussain, J., Khan, W. A., Khan, A. M., & Hayat, B. (2020). Tweets classification and sentiment analysis for personalized tweets recommendation. *Complexity*, *2020*(1), 8892552. doi: 10.1155/2020/8892552.

Mathariya, S. K., & Srivastava, H. (2023). A Review on Machine Learning Based Approaches for Automated Detection of COVID-19 Disease. In: Luhach, A.K., Jat, D.S., Ghosh, U., Gao, XZ., Lingras, P. (eds) Advanced Informatics for Computing Research. ICAICR 2023. Communications in Computer and Information Science, vol 2073. Springer, Cham. https://doi.org/10.1007/978-3-031-84059-3_4

Mohapatra, M., Nayak, M., & Mahapatra, S. (2022). A machine learning based drug recommendation system for health care. *Graduate Research in Engineering and Technology (GRET)*, *1*(6). doi: 10.47893/gret.2022.1109.

Nair, A. B., Jaison, D. T., & Anoop, V. S. (2024). " Hey..! This medicine made me sick": Sentiment Analysis of User-Generated Drug Reviews using Machine Learning Techniques. *arXiv preprint arXiv:2404.13057*. [Online]. Available: http://arxiv.org/abs/2404.13057

Nayak, S. K., Garanayak, M., Swain, S. K., Panda, S. K., & Godavarthi, D. (2023). An intelligent disease prediction and drug recommendation prototype by using multiple approaches of machine learning algorithms. *IEEE Access*, *11*, 99304-99318. doi: 10.1109/ACCESS.2023.3314332.

Nistal-Nuño, B. (2022). Medication recommendation system for online pharmacy using an adaptive user interface. *Computer Methods and Programs in Biomedicine Update*, *2*, 100077. doi: 10.1016/j.cmpbup.2022.100077.

Ochoa, J. G. D., Csiszár, O., & Schimper, T. (2021). Medical recommender systems based on continuous-valued logic and multi-criteria decision operators, using interpretable neural networks. *BMC medical informatics and decision making*, *21*, 1-15. doi: 10.1186/s12911-021-01553-3.

Paliwal, S., Mishra, A. K., Mishra, R. K., Nawaz, N., & Senthilkumar, M. (2022). XGBRS Framework Integrated with Word2Vec Sentiment Analysis for Augmented Drug Recommendation. *Computers, Materials & Continua*, *72*(3), 5345–5362. doi: 10.32604/cmc.2022.025858.

Posch, A., & Tiwari, P. (2021) Persona-Based Drug Recommender System using Online Reviews. doi: http://dx.doi.org/10.13140/RG.2.2.29049.19048.

Rani, S. S., Shilpa, P., & Menon, A. G. (2024). Enhancing Drug Recommendations: A Modified LSTM Approach in Intelligent Deep Learning Systems. *Procedia Computer Science*, *233*, 872-881. doi: 10.1016/j.procs.2024.03.276.

Rao, T. V. N., Unnisa, A., & Sreni, K. (2020). Medicine recommendation system based on patient reviews. *Int J Sci Technol Res*, *9*, 3308-3312.

Sboev, A., Sboeva, S., Moloshnikov, I., Gryaznov, A., Rybka, R., Naumov, A., ... & Ilyin, V. (2022). Analysis of the full-size russian corpus of internet drug reviews with complex ner labeling using deep learning neural networks and language models. Applied Sciences, 12(1), 491.

Shahbazi, Z., & Byun, Y. C. (2020). Toward social media content recommendation integrated with data science and machine learning approach for E-learners. Symmetry, 12(11), 1798., doi: 10.3390/sym12111798.

Sharma, D., Singh Aujla, G., & Bajaj, R. (2021). Deep neuro‐fuzzy approach for risk and severity prediction using recommendation systems in connected health care. *Transactions on Emerging Telecommunications Technologies*, *32*(7), e4159. doi: 10.1002/ett.4159.

Shiju, A., & He, Z. (2022, June). Classifying drug ratings using user reviews with transformer-based language models. In *2022 IEEE 10th International Conference on Healthcare Informatics (ICHI)* (pp. 163-169). IEEE. doi: 10.1109/ICHI54592.2022.00035.

Sivakumar, P., Nanthini, N., Suruthi, S., & Veronica, T. (2023). Drug Prescribing System Using Patient Reviews Based on Sentimental Analysis. *Journal of Coastal Life Medicine*, *11*(2), 1548–1555. .

Tran, D. H., Sheng, Q. Z., Zhang, W. E., Aljubairy, A., Zaib, M., Hamad, S. A., ... & Khoa, N. L. D. (2023). HeteGraph: graph learning in recommender systems via graph convolutional networks. *Neural Computing and Applications*, *35*(18), 13047-13063. doi: 10.1007/s00521-020-05667-z.

Vianny, D. M. M., Vaddadi, S. A., Karthikeyan, C., Shahid, M., Dhanapal, R., & Ravichand, M. (2023). Drug-based recommendation system based on deep learning approach for data optimization. *Soft Comput.,4*, 1–10. doi: 10.1007/s00500-023-08742-4.

Yan, Y., Yu, G., & Yan, X. (2020). Online doctor recommendation with convolutional neural network and sparse inputs. *Computational Intelligence and Neuroscience*, *2020*(1), 8826557. doi: 10.1155/2020/8826557.

Sandeep Kumar Mathariya
MEDICAPS University,
Indore, MP
India
mathariya@gmail.com
ORCID 0000-0002-3795-5455

Hemant Pathak
MEDICAPS University,
Indore, MP
India
pathakcombines@gmail.com
ORCID 0009-0003-0457-5274

Priyanka Kumrawat
MEDICAPS University,
Indore, MP
India
priu.kumrawat@gmail.com
ORCID 0009-0003-1531-7633

Digendra Singh
MEDICAPS University,
Indore, MP
India
dgndrasingh@gmail.com
ORCID 0009-0006-1043-3274

Mahaveer Jain
SAGE University,
Indore, MP
India
profmahavir@gmail.com
ORCID 0009-0006-0775-7817

Hemang Shrivastava
SAGE University,
Indore, MP
India
drhemang.shrivastava@sageuniversity.in
ORCID 0009-0003-2423-0628