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Research paper

A Modified Genetic Algorithm-Based Deep Learning Approach for Rainfall Category Prediction

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ABSTRACT

The Rainfall prediction is helpful in different fields like water management, energy supply, agriculture and others. The primary objective of rainfall prediction model is to accurately predict daily rainfall and assist in making significant decisions to tackle several challenges. In this paper, deep learning methodology has been coupled with a modified genetic algorithm to develop a Deep Learning Modified Genetic Algorithm (DLMGA) model. The goal of the model is to predict daily rainfall based on 28 years (1992 to 2020) of historical rainfall data. The performance of the DLMGA model is compared with that of the SDL (Simple Deep Learning) and DLGA (Deep Learning with Genetic Algorithm) models. An overall performance comparison of the SDL, DLGA and DLMGA models in terms of accuracy, precision, recall and f1-score reveals that the DLMGA model performs remarkably well in terms of prediction and has an impressive level of accuracy.

Keywords: Rainfall prediction, Deep learning, Genetic algorithm, Artificial Neural Network, Random Forest, Machine learning

Rainfall is a random occurrence and its prediction is essential for effective management in drought assessment, water management, in agricultural sector and other areas (Diop *et al.,* 2020). In India, agriculture is the primary occupation for 65% of the population who live in rural regions and rain is the main source of irrigation for agriculture (Nicholls, 2001). Thus, a significant effort is required to safeguard the severely affected Indian agriculture from any variation in rainfall patterns (Nema *et al.,* 2016). Rainfall prediction helps in making crucial decisions for managing water resources, enhanced agricultural productivity and crop selection.

In modern world, Artificial intelligence (AI) is a rapidly developing field of computer science research. Machine learning (ML) is a subset of AI that uses computerized algorithms to fix problems based on past performance without unnecessarily altering the basic process. (Solanki *et al.,* 2017). ML algorithms like Decision Tree, Naive Bayes, K-Nearest Neighbour, Random Forest, Support Vector Machine and others are used to build the models. In recent years, deep learning (DL), a subset of machine learning based on ANN, has grown in popularity and has been widely used for pattern recognition tasks (Matsuoka *et al.,* 2018). The deep learning approach is widely used in the fields of image recognition, bioinformatics, natural language processing, personal assistants, e-commerce and others (Hernández *et al.,* 2016).

The Artificial Neural Network (ANN) is a set of interconnected artificial neurons that can store and disseminate experiential knowledge to practitioners and researchers as an alternative tool (Arul Selvan & Miruna Joe Amali, 2024; Patel *et al.,* 2020). The ANN model's basic structure comprises an input layer, one or more hidden layers and an output layer. Each layer consists of one or more basic elements known as neurons. Data are introduced to the model at the input layer and then sent to the hidden layers for computation. Weights and bias modify data as it passes through each hidden layer neuron before it reaches the output layer. The activation function is used to identify whether or not a neuron is active, that is, whether or not the input from an essential neuron is utilized in the prediction process. Finally, the model results are produced at the output layers loss function is used to determine the loss or error of the model by comparing the result data with the original data (Zhao *et al.,* 2017).

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MSE, MAE, Hinge, Binary Cross Entropy, Categorical Cross Entropy and others are the various loss functions used to assess the model's error or loss (Rengasamy *et al.,* 2020; Wang *et al.,* 2020; Patel *et al.,* 2020).

The genetic algorithm is a search based optimization algorithm based on Charles Darwin's theory of 'Survival of the Fittest'. GA is inspired by how species evolve in nature through the natural selection of the fittest individuals to produce the best optimal solution (Sharma *et al.,* 2013). The best individual in the population will try to find an optimal solution by utilizing evolutionary operators such as selection, crossover, and mutation. This process starts with an initial population that was generated at random. The selection operator selects parents for mating based on their fitness and applies the crossover and mutation operators to produce new children in each generation. Finally, the fittest children replace the population's existing parents and the process repeats itself (Moslehi *et al.,* 2019).

The author (Patro & Bartakke, 2024) has developed a daily rainfall prediction model using long short term memory (LSTM). They made use of meteorological data gathered from January 2020 to September 2023 from AWS, which is situated in the Almora district of Uttarakhand. In order assess the LSTM approach, seven different models are created and evaluated by combining the parameters, such as activation functions, layers, epochs, etc. Lastly, it was suggested that LSTM model 7 provide the most accurate daily rainfall estimate.

In the present study, the authors (Zhao *et al.,* 2025) discuss the challenges involved in predicting urban rainfall. They developed a novel ensemble deep learning model that combines an upgraded whale optimisation algorithm (IWOA) with convolutional neural networks (CNN), long short term memory networks (LSTM), and a self-attention mechanism. While the LSTM detects long term correlations within the rainfall sequences, the CNN efficiently recovers hidden and invariant features from the rainfall data. The model's performance for daily rainfall prediction is demonstrated by its d-factor of 0.414, p-factor of 0.950, and NSE value of 0.83. For monthly rainfall prediction, the model gets an NSE value of 0.85, a d-factor of 0.827, and a p-factor of 0.883.

Deep learning (DL) is a powerful technique for prediction due to its ability to learn from large and complex datasets, along with automatic feature extraction. However, DL models can suffer from local minima, which reduce their accuracy. Genetic Algorithms (GA) are used to optimize neural network weights and help overcome this issue. Despite this, GA may face premature convergence, limiting its ability to find better solutions. To address this limitation, modifications to GA are required. Therefore, this work proposes a rainfall prediction model using DL combined with a modified GA for improved performance.

MATERIALS AND METHODS

Deep Learning Modified Genetic Algorithm [DLMGA] model has been developed by combining the power of deep learning which is excellent at extracting complex patterns from data with modified GA, which is renowned for its efficient parameter optimization. The flow chart for modified GA is depicted in Fig. 1. The DLMGA model's goal is to predict daily rainfall using 28 years (1992 to 2020) of preprocessed historical rainfall data. The Keras API framework is used to implement the DLMGA model. The architecture of a proposed DLMGA model is shown in Fig. 2.

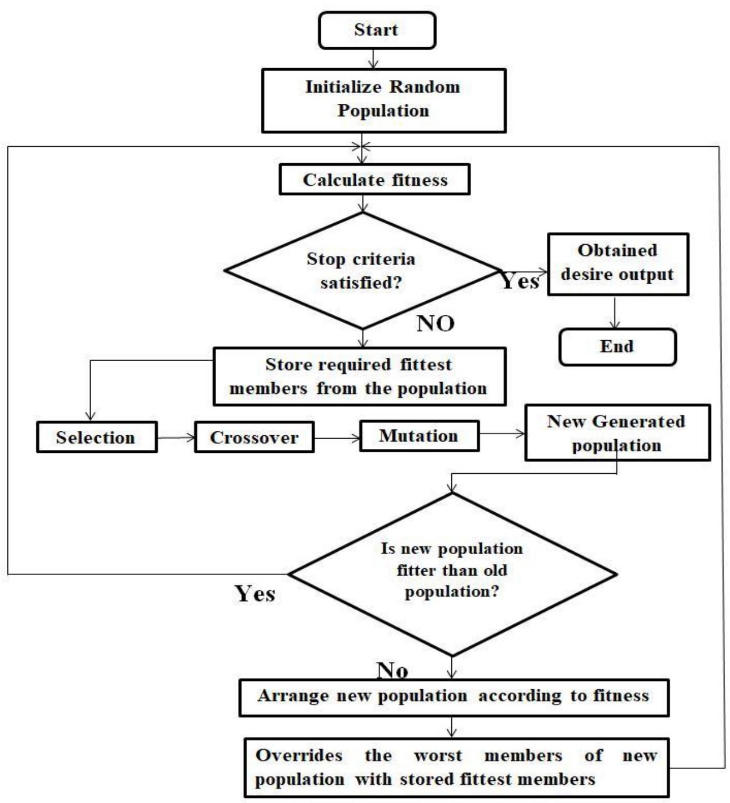

Fig. 1: Modified Genetic Algorithm flowchart depicting iterative fitness evaluation and replacement of worst individuals using previously stored best solutions

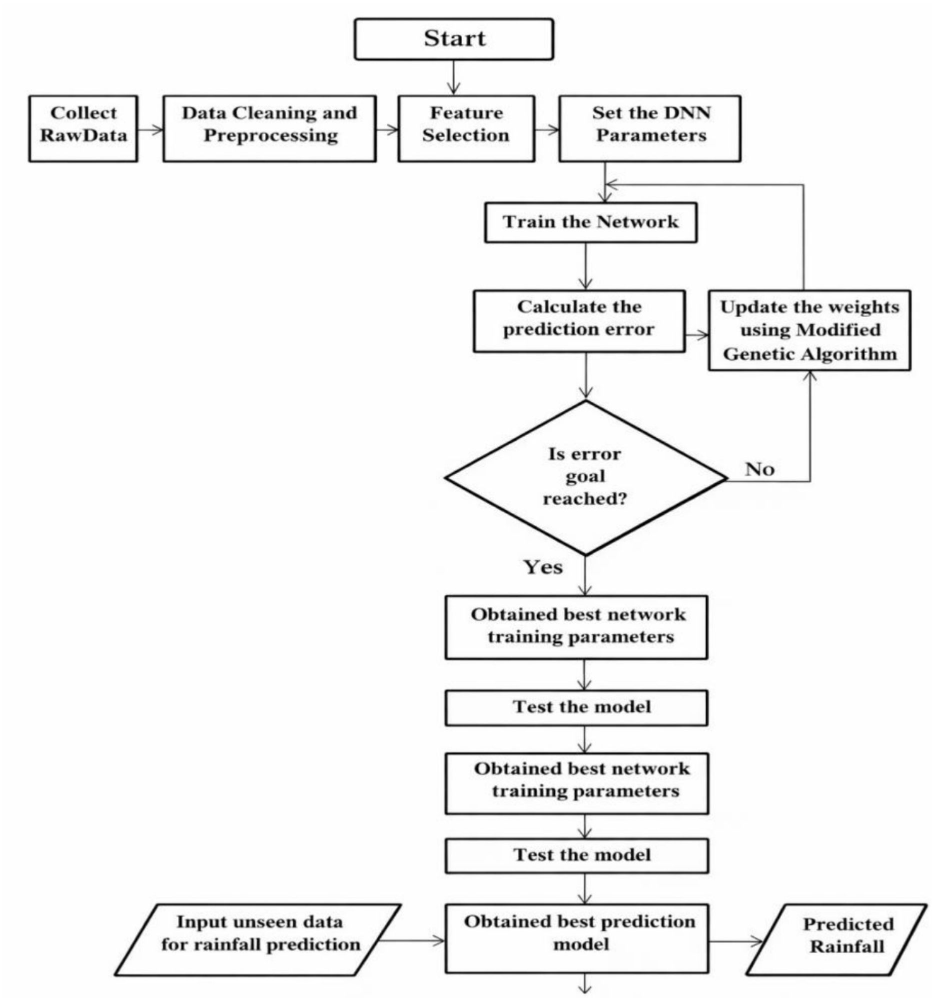

Fig. 2: Proposed hybrid DNN–Modified Genetic Algorithm framework for rainfall prediction showing preprocessing, training, error checking and optimized prediction

Modified Genetic Algorithm

The Genetic algorithm (GA) is a search based optimization algorithm based on Charles Darwin's theory of 'Survival of the Fittest'. This process starts with an initial population that was generated at random and performed selection, crossover and mutation until to evolved best individual in the population. GA struggles with premature convergence, which is surprisingly a result of the algorithm's efficiency, and it takes a long time to compute some complex problems due to its repeatedly adaptive evolution process. Thus it is vital to choose the best current generation solution to guide the GA to the global optimum. Therefore, in this study, a modified Genetic Algorithm has been developed to get over the drawbacks of standard GA. A modified Genetic Algorithm will store the best fittest members of the population. A new population is generated after the completion of all three genetic operations (selection, crossover and mutation). The members who are part of the new population are then compared with those of the previous population. If the new population has more fit members than the previous population, then the aforementioned three steps: fitness calculation, saving the fittest members and genetic operations are repeated until the stopping requirement is met. Otherwise, if the new population does not contain any members who are fit than the previous population, then all the individuals in the new population are arranged according to their fitness scores. After that, the worst fit members of the new population are substituted with the fittest saved members to create the updated set of the new population. Finally, the previous three steps: fitness calculation, saving fittest members and genetic operations are then repeated until the terminated criteria are satisfied.

EXPERIMENTAL DETAILS

Study location

The experiment was conducted by automatically collecting raw data from the agro-meteorological observatory at Navsari Agricultural University, Navsari, Gujarat. The model's in the study utilized raw data (10227 records) from 28 years (1992 to 2020) of daily rainfall in Navsari District. The daily rainfall data was split into two sets: training dataset and testing dataset, containing 70% (7158 records) and 30% (3069 records) of the total data. Furthermore, the training dataset is partitioned once again into 80% training records (5726 records) and 20% validation records (1432 records). Maximum temperature, Minimum temperature, Relative humidity (morning), Relative humidity (afternoon), Wind speed,

Table 1: Classes of Output Attributes

Sr. no.	Class Type	Rainfall Range (in mm)
1.	No rain	0
2.	Light rain	0.1 to 7.5
3.	Moderate rain	7.6 to 64.4
4.	Heavy rain	64.5 to 244.4
5.	Extremely Heavy rain	Above 244.4

Bright sunshine hour, Vapour pressure (morning), Vapour pressure (afternoon), Evaporation and Rainfall were used as input attributes. The output attribute is the rainfall type categorized into different classes mentioned in Table 1.

Data Preprocessing and Feature Selection

The data cleaning process was carried out, replacing any missing values with the mean value of the input parameters. After cleaning the data, it was scaled and normalized between [0–1], which improved training time (Patro & Bartakke, 2025; Ahmad & Aziz, 2019; Nayak *et al.,* 2014). The goal of feature selection is to choose the best features from the dataset. It helps to understand the data, reduce computing needs and improve performance. Several filters, wrappers and embedded methods are used for feature selection (Chandrashekar & Sahin, 2014). The model adopts Random Forest (RFM) as a feature selection method. The RFM helps to calculate the importance of features by neglecting the less useful ones from the dataset. The final input features selected using the Random Forest method include Maximum temperature (Tmax), Minimum temperature (Tmin), Relative humidity morning (RH1) , Relative humidity afternoon (RH2), Wind speed (WS), Bright sunshine hour (BSSH) and Evaporation (Evp), while the rainfall variable (Rf) is used solely for defining the output class and is not included as an input feature.

Building the prediction model

The Keras API framework was used to develop the proposed DLMGA prediction model. A deep neural network (DNN) employed by the prediction model consists of a single input and output layer, fully connected to three hidden layers and activation functions (Narvekar *et al.,* 2015). The best input features, determined by the feature selection algorithm, are fed into the model to form the input layer. The Rectified Linear Unit (ReLU) was utilized as an activation function in the model's hidden layers, which include 50, 30 and 18 neurons, respectively. Similarly, the Softmax activation function was employed by a model output layer. The model's loss or error is calculated using a categorical cross entropy loss function. The task of updating the weight of the neurons in each layer has been assigned to a modified GA to minimize model loss and error. The Genetic Algorithm hyperparameters were selected based on empirical tuning and prior literature. The population size was set to 50 with 100 generations. Rank based selection, single point crossover (0.8 probability), and random mutation (0.1 probability) were used. Additionally, elitism was introduced by retaining the top 10% fittest individuals to improve convergence. After obtaining the training prediction output, the model makes predictions on the validation set for each iteration or epoch of training. The validation set's actual target values are compared with the predictions. The validation accuracy is calculated to select the most accurate model based on model training. Additionally, it aids in avoiding overfitting of the model. The entire procedure is repeated until the maximum accuracy is achieved or the predetermined number of iterations has been reached. The model was appropriately trained and made ready for further use.

RESULTS AND DISCUSSION

DLMGA, SDL and DLGA models were evaluated and compared based on various performance metrics like accuracy, precision, recall and f1-score (Patel *et al.,* 2021). All models were implemented using the Keras framework to ensure consistency in architecture and training conditions, thereby enabling a fair comparative evaluation. The parameters used to train this model are described in Table 2 and 3.

Experimental Result for the DLMGA model

The training and validation accuracy trends of the DLMGA model shown in Fig. 3 demonstrate stable convergence behavior, with a minimal gap between the two curves. This indicates that the model effectively generalizes to unseen data and is not affected by overfitting.

The superior performance of the proposed Deep Learning Modified Genetic Algorithm (DLMGA) model can be attributed to several factors. First, the Modified Genetic Algorithm improves weight initialization and optimization, enabling the deep learning model to converge more effectively. Second, the introduction of elitism (retaining top 10% of fittest individuals) ensures preservation of optimal solutions across generations, improving convergence stability. Third, the use of crossover and mutation operations enhances exploration of the search space which help to avoid local minima, a common issue in deep learning training. Furthermore, the hybrid approach combines the learning capability of deep neural networks with the global optimization strength of genetic algorithms, leading to improved prediction accuracy and reduced error metrics. These factors collectively contribute to the superior performance of the DLMGA model compared to conventional deep learning and other baseline approaches."

Once the model had been successfully trained and validated, it was tested using the testing dataset. The number of true and false prediction records must be determined in order to compute the training and testing accuracy. Table 4 below shows the accurate and incorrect prediction record of the DLMGA model with its accuracy.

The confusion matrix of the DLMGA model is created to determine the model's accuracy, precision, recall and f1-score. The DLMGA model's confusion matrix with five output class types "No Rain"," Light rain", " Moderate rain", " Heavy rain" and " Extremely heavy rain" is shown in Table 6.

The model's classification report is generated based on the confusion matrix, which shows the precision, recall and f1-score values for each output class type separately. These metrics assist in identifying the pros and cons of the model's performance across various classes, which helps in evaluating the model and considering possible enhancements.

Table 2: A description of the deep learning parameters

Name	Description	SDL	DLGA	DLMGA
Input parameter	Input features used in the model	7	7	7
Epoch	The number of iterations or generations that the model used to modify the weights during training	500	500	500
Activation function	It decides whether a neuron is active or not for the model's prediction based on a set of inputs that define the output of that neuron.	ReLU (hidden layers) Softmax (output layer)	ReLU (hidden layers) Softmax (output layer)	ReLU (hidden layers) Softmax (output layer)
Optimizer	It is used to update the model's weights in order to minimize loss/error.	Adam	GA	Modified GA
Loss function	It is used to determine the model's loss/error.	Categorical cross entropy	Categorical cross entropy	Categorical cross entropy
Output parameter	Output parameter used in the model	1	1	1
Input parameter	Input features used in the model	7	7	7

Table 3: A description of Genetic Algorithm parameters

Name	Description	DLGA	DLMGA
Initial population	Random initialization of neural network weights	Random weights	Random weights
Population Size	Number of individuals in each generation	50	50
Chromosome Representation	Encoding of solution	Encoding of solution	Encoding of solution
Parent selection	Method for selecting parents	Rank method	Rank method
Crossover	Recombination method	Single point crossover	Single point crossover
Crossover Probability	Probability of applying crossover	0.8	0.8
Mutation	Method to introduce variation	Random resetting	Random resetting
Mutation Probability	Probability of mutation	0.1	0.1
Number of Generations	Total iterations of GA	100	100
Termination Criteria	Stopping condition	Max generations or convergence	Max generations or convergence
Fit parents	It retains the population's fittest parents for use in the future.	Not applied	10%
Fitness function	Evaluation criterion	Inverse of categorical cross entropy loss	Inverse of categorical cross entropy loss
GA–DL Interaction	Integration with neural network training	Optimizes network weights	Optimizes network weights with Fit Parents

Table 5 presents the classification performance of the DLMGA model across different rainfall classes. The model achieves strong performance for the "No rain" category, which is the most dominant class in the dataset, while maintaining balanced and consistent performance across "Light rain," "Moderate rain," and "Heavy rain" categories. This indicates that the model is capable of capturing diverse rainfall patterns effectively. The overall weighted F1-score further reflects stable predictive performance; however, a detailed class wise evaluation provides a more comprehensive understanding of model behavior across different rainfall intensities.

Despite the improved performance of the proposed DLMGA model, certain limitations exist. First, the integration of deep learning with a modified genetic algorithm increases computational complexity and training time, particularly when multiple generations and larger population sizes are used. This may require higher computational resources compared to conventional deep learning models. Second, the model relies heavily on historical local meteorological data, which may limit its generalization capability when applied to different geographical regions with varying climatic patterns. Third, the optimization process may be sensitive to hyper parameters selection such as population size, mutation rate, and crossover rate, which may affect model performance. Future work may focus on reducing computational cost, incorporating transfer learning techniques, and using multi region meteorological datasets to improve model generalization and scalability.

Performance Comparative Analysis

The results obtained from the proposed DLMGA model were compared with the SDL and DLGA models. It is crucial to analyze the training and testing accuracy of these models in order to evaluate their performance. The training accuracy of the SDL,

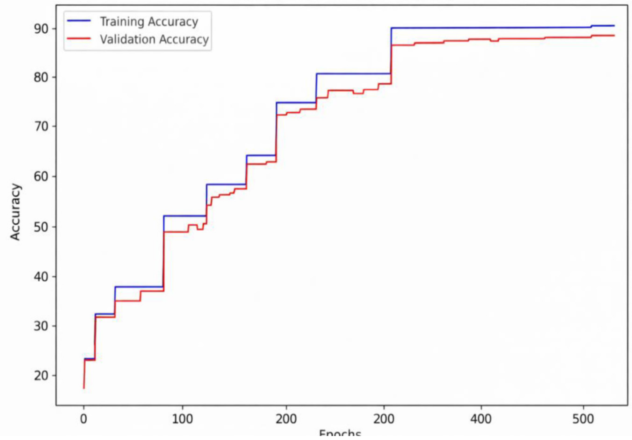

Fig. 3: Iteration wise training and validation accuracy of the DLMGA model demonstrating convergence behavior and consistency between training and validation performance.

Table 4: True and false prediction records of the DLMGA model

	Total Records	True Prediction	False Prediction	Accuracy
Training	5726	5255	471	91.78 %
Testing	3069	2737	332	89.18%

Table 5: Classification report of DLMGA model

Rainfall Type	Precision	Recall	F1-score	Support
No Rain	0.95	0.95	0.95	2393
Light Rain	0.65	0.70	0.67	320
Moderate rain	0.70	0.67	0.68	297
Heavy rain	0.73	0.69	0.71	58
Extremely Heavy rain	0.00	0.00	0.00	1
Weighted Average	0.89	0.89	0.89	-

DLGA, and DLMGA models is compared in Fig. 4. The data showed that the proposed DLMGA model has a training accuracy of 91.78% compared to 86.42% of the DLGA model and 74.45% of the SDL model. The graph demonstrates the optimal result for the best model training accuracy.

Similarly Fig. 5 compares the testing accuracy of the SDL, DLGA and DLMGA models. The DLMGA model achieved a testing accuracy of 89.18%, representing an improvement of 4.08% over DLGA and 14.70% over SDL. This consistent performance across training and testing phases indicates strong generalization capability and reduced overfitting. These results demonstrate that the proposed hybrid approach not only improves accuracy but also enhances model stability, making it more reliable for real world rainfall prediction tasks.

We have also evaluated the precision, recall and f1-score for each output class type separately for the SDL, DLGA, and DLGMA models in our multiclass rainfall prediction problem. This enables us to comprehend the model's performance for each class of rainfall type. The output class types "No rain," "Light rain," "Moderate rain" and "Heavy rain" are compared in terms of precision, recall, and f1-score below in Fig. 6, 7, 8 and 9 respectively.

From the below comparison, we can determine that all three models are very accurate at predicting "No rain" and perform reasonably well for "Heavy rain." However, the SDL model perform poorly for "Light rain" and "Moderate rain" when compared to the DLGA and DLMGA models. In addition, the DLMGA model outperforms the SDL and DLGA models in terms of precision, recall, and balanced F1 score for each separate output class type.

To further validate the statistical significance of the proposed DLMGA model, a paired t-test was performed between DLMGA and baseline models across multiple runs. The results showed that the improvement achieved by DLMGA is statistically significant at a 95% confidence level ($p < 0.05$). This confirms that the superior performance of the proposed model is not due

Table 6: Confusion matrix-based class-wise classification performance of the proposed DLMGA model for multiclass daily rainfall prediction.

Class types	No rain	Light rain	Moderate rain	Heavy rain	Extremely Heavy rain
No rain	2276	81	36	0	0
Light rain	63	223	34	0	0
Moderate rain	46	39	198	14	0
Heavy rain	0	2	16	40	0
Extremely Heavy rain	0	0	0	1	0

Fig. 4: Training accuracy comparison of SDL, DLGA and DLMGA rainfall prediction models

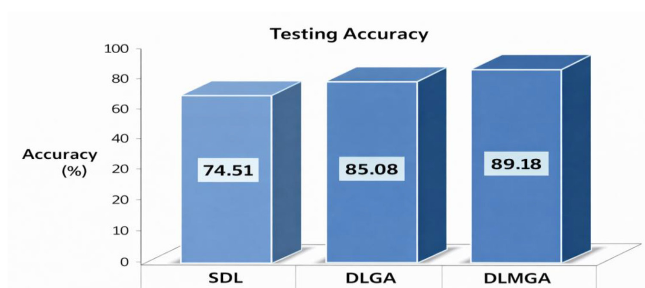

Fig. 5: Testing accuracy comparison of SDL, DLGA and DLMGA rainfall prediction models

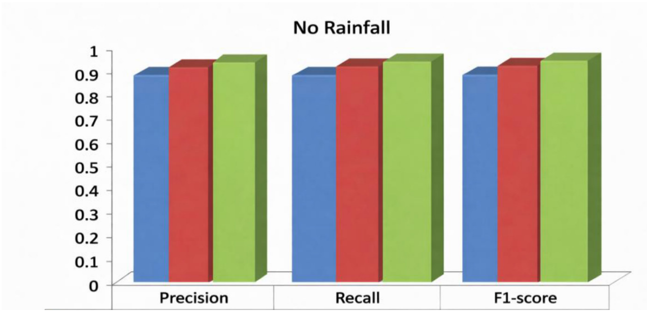

Fig. 6: Performance comparison for the "No Rain" using precision, recall and F1-score

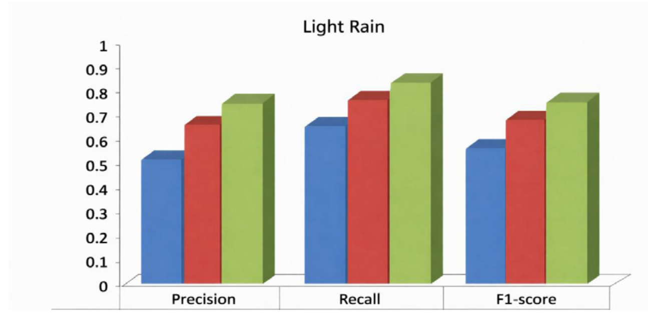

Fig. 7: Performance comparison for the "Light rain" using precision, recall an d F1-score

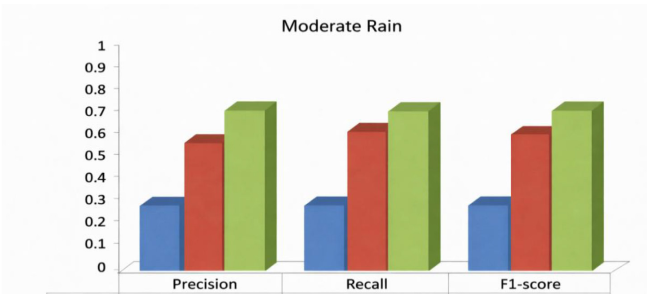

Fig. 8: Performance comparison for the "Moderate rain" using precision, recall and F1-score

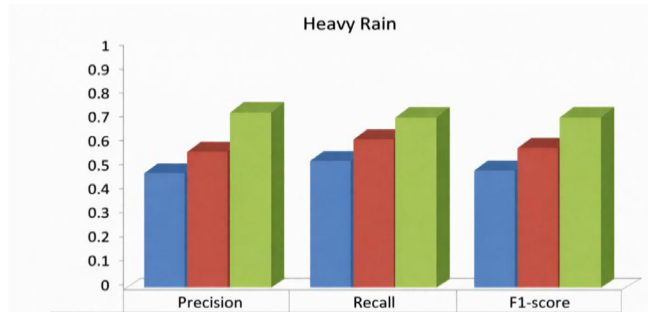

Fig. 9: Performance comparison for the "Heavy rain" using precision, recall and F1-score

to random variation but due to effective optimization using the modified genetic algorithm.

CONCLUSION

DLMGA rainfall prediction model has been developed which integrates the deep learning approach with modified genetic algorithm. The performance of DLMGA was compared with the SDL and DLGA models. The Keras API framework was utilized to build these models. These models were trained, validated and tested using 28 years (1992 to 2020) of daily rainfall data from the Navsari district. The Random Forest is used as a feature selection method to select the most relevant and effective features for the models. The modified genetic algorithm was used to update the weights of the deep neural network neurons after the DLMGA model's parameters were set up. The DLMGA model has been evaluated using various performance metrics like accuracy, precision, recall and f1-score. The DLMGA model can be used to make daily rainfall prediction which can be beneficial in taking crucial decisions for managing water resources, agricultural productivity and crop selection.

The accuracy of the three models SDL, DLGA, and DLMGA was 74.49%, 85.07%, and 89.15%, respectively. Thus DLMGA model performed better than the other two models. For each output class types the comparison of accuracy, precision, recall and f1-score was done and it was found that all three models are very accurate at predicting "No rain" and perform reasonably well for "Heavy rain." However, the use of random train-test splitting may introduce potential temporal linkage and optimistic performance. This limitation can be overcome by using time-ordered validation strategies which can be included in the future work. Also, the SDL model perform poorly for "Light rain" and "Moderate rain" when compared to the DLGA and DLMGA models. Thus, from the overall performance comparison of the SDL, DLGA and DLMGA models in terms of accuracy, precision, recall and f1-score, it can be concluded that the DLMGA model has an appreciable level of accuracy and gives better prediction results. Thus, modified genetic algorithm was capable in generating better results.

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