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Original Article

Deep Web Content Mining for Personalized Web Search: An Application of Optimized Fuzzy Ensemble of CNN Models

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Abstract *- A novel design is proposed for Personalized web search based on web document classification using a Fuzzy ensemble of CNN models with Genetic Algorithm(GA) based hyperparameter optimization. The hyperparameter optimization of CNN is done using GA to improve the classification accuracy. The proposed ensemble model combines the advantages of ensemble and a Fuzzy weighted combination of deep learning models that classifies web documents into five classes, mainly politics, sports, technology, entertainment, and business. The performance of the fuzzy ensemble of CNN classifiers with GA based hyperparameter optimization was compared with other state-of-the-art models. The use of the proposed approach displays a significant improvement in the web document classification accuracy. The web documents classified based on the proposed method are grouped together in clusters for personalized web search, and the average precision of the search results is improved significantly.*

Keywords *- Ensemble Deep Learning, Genetic Algorithm(GA), Hyperparameters Optimization, Web document recommendation, classification, Convolution Neural Network (CNN), Personalized Web Search (PWS).*

1. Introduction

The Multilingual text classification was proposed based on an ensemble method, and the results displayed significant performance. Deep Ensemble learning combines the advantages of deep and ensemble learning. Convolutional Neural Network (CNN) because of its powerful architecture has applications in various domains like computer vision, facial recognition, Computer-Aided Diagnosis (CAD), Natural Language Processing (NLP), sentiment analysis, pattern recognition [28], medical imaging, classification [29, 30], detection [31, 32], and segmentation [33, 34] etc. Recent research has found that the deep learning model CNN displays significant performance in text classification. The objective of an ensemble deep learning is to improve the classification accuracy by combining the predictions of individual neural network models. Ensemble learning displays significant performance in enhancing the classification accuracy. CNNs are sensitive to hyperparameters; therefore, CNNs with different configurations of their hyperparameters are used successfully as base classifiers in an ensemble model. The text classification using an ensemble displays significant performance using feature extraction techniques [2]. There are various factors that affect the accuracy of the ensemble deep learning systems, such as the selection of the baseline deep learning model, the number of baseline models used, the training-test data set ratio for training an ensemble system, and the fuzzy weighted fusion method for aggregating the output of baseline classifiers in an ensemble. The hyperparameters of the deep learning model CNN are of two types: network structure parameters and network training parameters. The network structure parameter includes filters, kernel size, hidden layer, and activation function. The network training includes learning rate, batch size, momentum, epoch, and optimizer [3]. Hyperparameter optimization is a method of searching for the optimal values of hyperparameters that give the maximum classification accuracy of the CNN model on the data set, subject to the minimization of the loss function based on predicted and actual output of the classifier. The training of CNN is costly because of the huge number of hyperparameters of the network. It is computationally expensive to search for the optimal values of hyperparameters. Therefore, there is a need for an automated method of hyperparameter optimization during training of the CNN model. The genetic algorithm has been applied successfully in research to optimize network structure and network training parameters. Therefore, GA is used for hyperparameter optimization of CNN for increasing the accuracy of classification. [4-6] GA has been selected for optimization as it does not have a suboptimal local maximum/minimum problem [7-10].

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The genetic algorithm is considered the guided random search. Genetic Algorithm is an evolutionary method, and the randomness in the algorithm is controlled based on the selection of values for crossover, mutation, and selection. A genetic algorithm has been used for the optimization of hyperparameter network structure and network training parameters because of its advantage in that it does not get trapped in local minima [11, 12].

A novel approach is used for web document classification using a fuzzy ensemble of a CNN model with Genetic Algorithm-based hyperparameter optimization. The hyperparameter optimization of CNN using GA in the training process significantly impacts the classification accuracy. The homogeneous ensemble deep learning model is used because of its simplicity and ease of use. The hyperparameters of the baseline CNN models are varied for the diversity in the baseline models in order to use them in an ensemble model. Thus, the use of different structures of the baseline CNN models in an ensemble reduces the number of hyperparameters for training. Genetic algorithm do not get trapped in local maxima or minima. Therefore, GA-based hyperparameter optimization of CNN is used in an ensemble for improving the web document classification to five classes: mainly politics, sports, technology, entertainment, and business.

The web documents classified using the proposed method are clustered based on class labels and are further used for personalized web search. The web document classification using a fuzzy ensemble of CNN with GA-based hyperparameter optimization is compared with other state-of-the-art models. The classification accuracy using the proposed method is improved significantly due to the application of fuzzy fusion of the output of GA GA-optimized CNN model in an ensemble in order to generate the prediction with high classification accuracy. The classification accuracy will be high as the output of an ensemble is based on the weighted average prediction of the individual optimized classifier. Thus, the use of individual classifier accuracy as the fuzzy weights in the average voting method increases the prediction accuracy of the ensemble model, assuming all the models are not equally accurate to contribute to the prediction of the final output. Fuzzy ensemble of CNN models' performance is compared to state-of-the-art models and an ensemble of CNN models, and results confirm the improvement in accuracy and average precision using the proposed method.

2. Related Work

Ensemble techniques for classification use the multiple baseline classifier. Therefore, multiple models are trained for a particular task. The output of the baseline classifier is combined using fusion methods like majority voting, weighted majority voting, etc. Hence, it generates a robust classifier for classification. Ensemble learning has been applied successfully for outlier detection and the class imbalance problem in medical data sets. [13, 14] Ensemble Deep learning models are applied in various fields such as heart disease detection on ECG, predicting a brain disorder, early detection of kidney stones, detecting online fraud, and show the classification accuracy of 95.8%. AdaBoost, ANN, random forest, and logistic regression are used in the ensemble learning method to predict Covid-19 efficiently, credit card fraud detection, etc. A genetic algorithm is used for feature selection, and the selected features are used for training an ensemble [15, 16].

Deep learning based ensemble learning was used to analyze the COVID-19-related sentiments. The proposed approach displays a superior accuracy of 87.8% in comparison to similar state-of-the-art methods. [17] The ensemble learning method was used to predict fake news reports. The experiment results display an accuracy of 99%. [18] An ensemble of 6 ML deep learning algorithms was applied using stacking as a fusion method. It was concluded that the ensemble technique displays better classification results in comparison to the individual models. [19]. An ensemble of CNN models with different hyperparameter settings captures different aspects of an image representation and displays significant performance in comparison to an individual deep learning model. An ensemble of CNN models obtains better feature extraction from medical images than a single CNN model [20].

The training of CNN models in an ensemble is computationally expensive, as it involves optimization of hyperparameters for improving the classification of an ensemble. The size of hyperparameters is huge for optimization; therefore, training a deep neural network is computationally expensive in comparison to a traditional classifier. Thus, the use of the same baseline models with different structures reduces the size of hyperparameters during the training of an ensemble and displays significant performance. Various fusion techniques like stacking, boosting, and voting methods are applied on the output of multiple CNNs in an ensemble during the model training on various data sets like CIFAR-10 and healthcare data (tuberculosis detection, neuromuscular disorder detection). [1] [21-25] The ensemble model has been applied in the field of robotics and displays significant performance [26].

An optimization technique, the Genetic algorithm works on the principle of the natural theory of evolution and solves the problem using a chromosome representation that represents the possible solution to the problem. A fitness function is a measure to assess the quality of a chromosome. Therefore, the population of chromosomes is generated, and the fitness function is calculated to associate a significant value with a given chromosome. The genetic operators are applied to the chromosome selected based on fitness value using selection techniques like the tournament method, the roulette wheel selection method, etc. The application of genetic operators on the selected chromosomes introduces diversity in the population of chromosomes and prevents the genetic algorithm from local optima. The process of selecting the chromosome based on fitness value and application of genetic operators continues till the maximum fitness value is obtained or the maximum number of generations is reached.

The goal of hyperparameter optimization is the tuning of hyperparameters like network structure parameters and network learning parameters in the CNN model during training in order to determine the optimal value of hyperparameters that gives the maximum classification accuracy of the CNN model. The hyperparameters that yield the optimal performance of CNN involve training the CNN model multiple times for a given set of hyperparameters, which is computationally expensive. Techniques, like random search, grid search, Hessian-free optimization [39], genetic algorithms [40, 36–38], Bayesian optimization [35], hyperband [41], and the Asynchronous Successive Halving Algorithm (ASHA) [42, 43] have been developed for hyperparameter optimization.

Metaheuristic algorithms display significant performance in generating the optimal values of hyperparameters. The Firefly, Harmony Search (HS), Particle Swarm Optimization (PSO), and Ant Colony Optimization (ACO) method displays an accuracy of 96.7%, 95.03%, 89.5%, and 89.79% respectively. [45, 46] [48, 49] Bayesian Optimization, Grey Wolf Differential Evolution, Genetic Algorithm, and Firefly Algorithm were implemented on the medical image data set. The results confirm the effectiveness of these algorithms in exploring optimal hyperparameter combinations for medical images. Recently, methods have been developed for CNN hyperparameter optimization using algorithms, such as Genetic Algorithms (GAs), for classification [44]. [6, 50] GA is selected for hyperparameter optimization of CNN to increase the accuracy of classification.[47] GA has been selected for optimization as it does not have a suboptimal local maximum or minimum problem. [51-53]. Genetic Algorithm has been applied in hyperparameter optimization of CNN models, where chromosomes represent the values for selected hyperparameters of CNN models. [27] Research has been done for personalised web search. In this research, a novel approach using a fuzzy ensemble of CNN models is proposed for personalized web search.

3. Proposed Approach

A novel technique is proposed in this paper for intelligent web content mining using a fuzzy ensemble of CNN with GA-based hyperparameter optimization. The training data of web document content is preprocessed using Word2Vec and then input to an ensemble of CNN models for fine-tuning the hyperparameters of CNN models with the objective of improving the accuracy of the ensemble. The classification accuracy of the trained CNN models on the testing dataset is calculated and used as a weighted sum in the fuzzy fusion of the outputs of individual models within the ensemble. CNN has been applied in various domains like image classification, Arabic handwritten recognition, etc. The deep learning model CNN learns patterns from the data using a complex degree of abstraction without human intervention. A Convolution Neural Network has convolution layers that use multiple filters and max pooling to obtain an abstract representation of the input that captures features of interest. The nonlinear transformation is applied using an activation function. The fully connected layer maps the extracted feature to a single-dimensional feature set. These extracted features are classified at the output layer using a suitable activation function like softmax, which is commonly used.

During the training of CNN models for classification, hyperparameter values are tuned to increase the accuracy of classification. The optimization of hyperparameters is costly due to the huge number of hyperparameters; therefore, the ensemble of multiple same baseline models configured with different value of hyperparameters is trained on a given data set for classification. The use of the same baseline model with different configurations of hyperparameter values reduces the number of hyperparameters for optimization during the training of an ensemble.

There is a huge computation involved in determining the optimal values of hyperparameters. Therefore, GA is used for hyperparameter optimization of CNN for increasing the accuracy of classification. GA has been selected for optimization as it does not have a suboptimal local maximum or minimum problem.

Thus, a novel approach for deep web content mining using a fuzzy ensemble of CNN deep learning models with GA-based hyperparameter optimization is proposed for effective personalized web search. Three CNN models were trained with hyperparameters optimized using GA, and the outputs of multiple CNNs for a given class are combined using the fuzzy ensemble technique based on the weighted average voting ensemble as given in the equation below.

$$\mathbf{F(e1, e2, .. en)} = \frac{\sum_{i=1}^{n} \mathbf{w_i * pred(e_i)}}{\sum_{i=1}^{n} \mathbf{w_i}} \qquad (1)$$

Where F is the fuzzy fusion of the prediction of CNN models $e_1, e_2, \ldots . e_n$ (n=3) in an ensemble weighted by w_i (classification accuracy). The framework design of the technique proposed in this paper is illustrated in Figure 1 below.

The training of the model has been done individually for the sample of the given datasets before combining them. The accuracy of the trained model is used as a fuzzy weight to provide different weightage to the prediction of the base classifier in an ensemble.

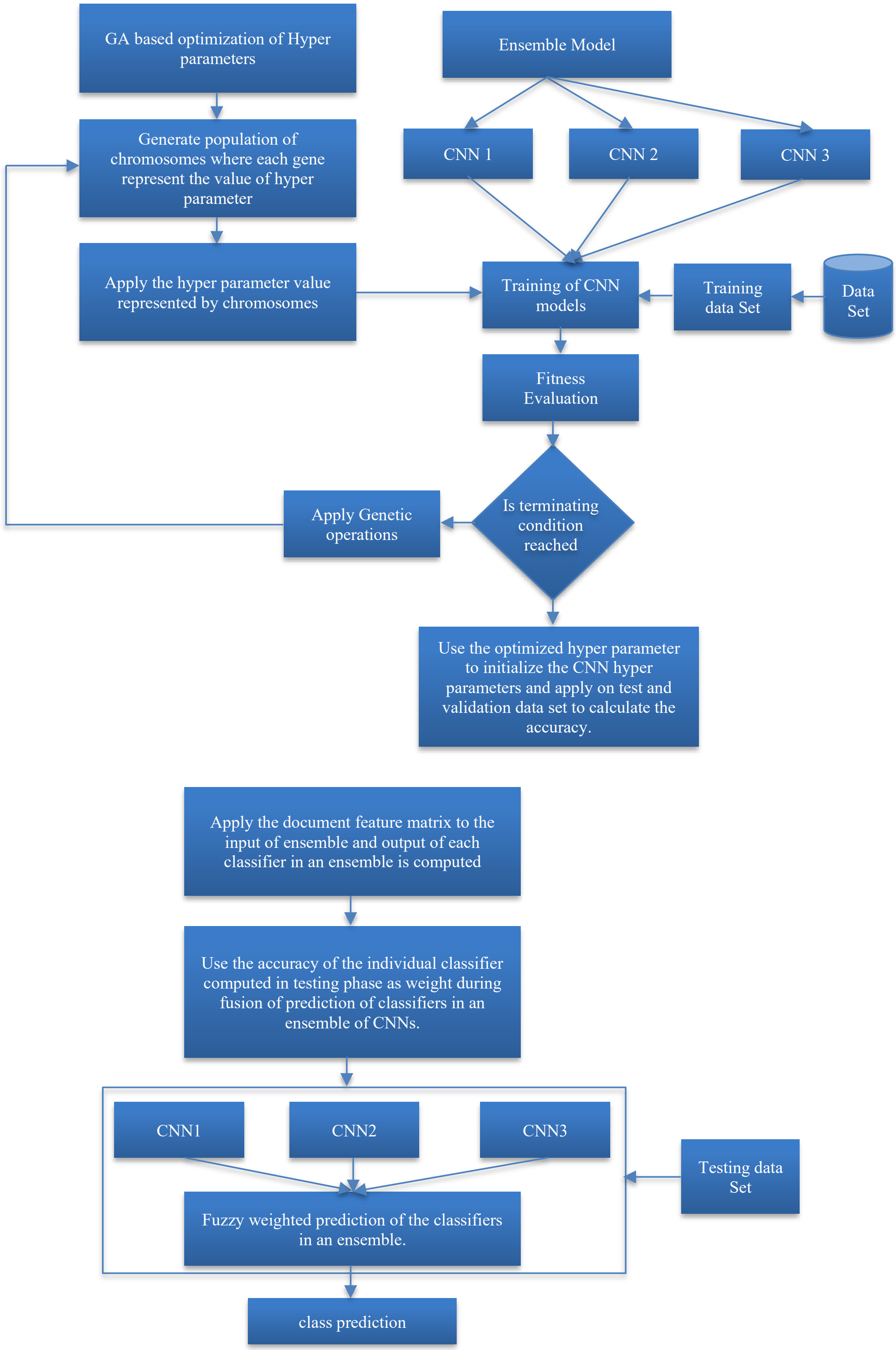

Fig. 1 Flowchart of Fuzzy ensemble deep learning approach with GA based hyperparameter optimization for web document classification

The weighted average prediction of an ensemble is obtained by the product of the classifier's prediction by the fuzzy weight of the classifiers (its classification accuracy), normalized by the sum of the weights of the classifiers. The weighted average prediction is used to predict the output class of the ensemble model. Thus, the use of individual classifier accuracy as the fuzzy weights in the average voting method increases the accuracy of the ensemble model.

3.1. Chromosome Design

The chromosome size is the same as the number of hyperparameters to be optimized. In this paper, 10 hyperparameters are selected for optimization. The chromosome representing the hyperparameters selected for optimization is mentioned below in Table 1. The possible range of parameter values is mentioned below in Table 1.

Table 1 . Hyperparameters and range of values for CNN model optimization

Filters 1	Filters 2	Filter 3	ksize	Activation 1	Activation 2	D1	D2	op	ep

S.No	HyperParameter	Abbreviation	Range
1.	Number of Filters(layer1)	Filters1	[32,64]
2.	Number of filters(layer2)	Filters2	[32,64]
3.	Number of filters(layer 3)	Filters3	[128, 256, 512]
4.	Kernel size	ksize	[2,3]
5.	Activation Function	Activation1	[‘relu’,’selu’,’elu’]
6.	Activation Function	Activation2	[‘relu’,’selu’,’elu’]
7.	Dropout	D1	[0.1,0.5]
8.	Dropout	D2	[0.1,0.5]
9.	Optimizer	op	["adamax", "adadelta", "adam", "adagrad"]
10.	Epoch	ep	[5,10]
11.	Learning rate	learning_rates	[0.001]
12.	Batch Size	batch_sizes	[50]

The GA parameter setting for the hyperparameter optimization is given below in Table 2.

Table 2. Genetic algorithm parameter values for optimization

No. of Generations	10
Size of the Population	25
Crossover Probability	0.8
Mutation Probability	0.02
Selection Method	Roulette wheel selection
Crossover function	One point
Mutation operator	Point
Fitness function	CategoricalCrossentropy

3.2. Working of the Proposed System

The hyperparameter optimization of the individual CNN is done using GA based on the chromosomes, where each chromosome is a collection of genes, and a gene is initialized randomly using values in the range for the selected parameter. A total of 10 hyperparameters were selected for optimization and represented by genes in the chromosome.

During the training, the hyperparameters represented by the chromosome are applied to the individual CNN model, and the fitness value is computed. Genetic operators are applied to the chromosome selected using roulette wheel selection based on fitness value, and the current population of chromosomes is replaced. Thus, the training of CNN models is continued until the accuracy of the model reaches its maximum or the maximum generation limit is reached. Thus, upon termination of GA-based optimization of the hyperparameters, the chromosome with a maximum fitness value is selected for the given CNN model hyperparameter initialization. This process of GA based hyperparameter optimization and training is done for each of the individual CNN models in an ensemble. The trained CNN model initialized with optimized hyperparameters is tested on the test data set, and the accuracy of the individual model is obtained.

The accuracy metric is mentioned below.

$$\text{Accuracy} = (TP+TN) / (TP+FP+TN+FN) \quad (2)$$

Where,
TP: True positive

TN: True negative

FN: False Negative

FP: False Positive

In the proposed method, the fuzzy ensemble approach, a weighted average voting is used where the accuracy of the trained individual model is used as the weight of the individual classifier. Weighted average voting combines the individual model class predictions for the final prediction and overcomes the disadvantage of hard voting, where all the models in an ensemble are given equal weightage despite the fact that a given classifier is weak.

The algorithm designed for the proposed approach is implemented in two phases: offline and online. The details of offline processing and online processing are given as follows in Algorithm 1 and Algorithm 2.

Algorithm 1: Steps for Offline Processing for Web Document Classification using Fuzzy Ensemble of CNN with GA based optimization.

GA_Hyperparameter_Optimization
Input: Web documents, CNN1, CNN2, CNN3
Output: Trained Ensemble of CNN1, CNN2, CNN3.

- Generate the collection of chromosomes where a chromosome is comprised of genes, and each gene represents the possible value of the selected hyperparameter.
- The length of chromosomes and the number of hyperparameters selected for optimization.

For each CNN model:
Repeat the following:

1. Apply the hyperparameter values represented by genes of the chromosomes to the individual model of the ensemble and calculate the fitness function value.
2. Calculate the fitness value of chromosomes and select the chromosomes based on fitness value using roulette wheel selection. Elitism is used to replicate the best chromosome without using genetic operators.
3. Genetic operators are applied on the selected chromosomes with a mutation probability of 0.02and a crossover rate of 0.8.
4. A steady state, with no duplicate replacement policy, is applied to generate the next generation of population by replacing the parent chromosomes with their child chromosomes, as obtained in step 2. Until the number of generations reaches 10 or maximum accuracy is obtained.

- Upon termination, the chromosome with the fitness value greater than the threshold is used for hyperparameter initialization of respective CNN1, CNN2, and CNN3.
- CNNs initialized with optimized hyperparameters are evaluated on the test data set to find their individual accuracy after training. The accuracy is calculated using the confusion matrix of the individual model on the same test data set.
- The accuracy score of the individual model will be used as fuzzy weights in the weighted sum of class prediction at the output of the ensemble.
- The weighted prediction output of the ensemble is generated at the output for the final web document classification.
- The trained and tested ensemble CNN model is used for web document classification into the predefined categories Politics, Sport, Technology, Entertainment, and Business.
- The web documents belonging to a similar class are clustered in groups, and the cluster centroid is represented by the mean of the document keyword vector present in that group.
- The resulting clusters of optimal web document feature vectors based on their class labels are used for PWS during online processing.

Algorithm 2: Recommendation of web documents for Personalized Web Search (Online Processing)

Online Processing;

1. Generation of clusters of Web documents based on class labels generated in offline processing.
2. Computation of the cluster's mean vectors.
3. The selection of the cluster is based on a web search query with maximum similarity with the cluster means.
4. The selected cluster is used to recommend web documents.
5. Compute the user search session Word2Vec average feature vector using the recommended web documents clicked by the user.
6. Repeat::
   - Select the cluster whose means are most similar to the user search session mean vector.
   - Use the selected cluster to recommend web document recommendations for the next web page request.
   - Go to step 5, until there is no request for the next search page.

The web documents classified using the proposed approach are clustered based on their class label. The content vectors of web documents in a given cluster are averaged to represent the cluster mean. The cluster is selected for personalized web search based on web document recommendations.

4. Experiment Study

The proposed method was implemented on the text data set available publicly on Kaggle using an Intel Core i7 3.80 GHz with TensorFlow in the Python environment.

The experiment results were compared with many existing methods, and the proposed approach displays a significant improvement in the classification accuracy.

4.1. Dataset

In the current research, publicly available benchmark datasets downloaded from Kaggle https://www.kaggle.com/datasets/sunilthite/text-document-classification-dataset are used. The dataset contains 2225 text data belonging to the domains politics, sport, technology, entertainment, and business. The details of the dataset are given in Table 3 below. The NLTK library was used to process the content of web documents (stopword removal, delimiter removal, etc.) and generate the web documents' word vectors.

Table 3. Data set: sample distribution in the predefined category

Class	Category	Number of samples
0	Politics	417
1	Sport	511
2	Technology	401
3	Entertainment	386
4	Business	510

The dataset is split into distinct training, test, and validation subsets. The percentages of the train, test, and validation data sets are as follows: 75%, 15% and 10% of the whole data set. k k-fold cross-validation method, where k=5, was used, and a classifier was tested on each fold.

The classifier was trained using a training data set, and a first-level classifier was obtained. The first-level classifier was trained on the validation data set, and the second-level classifier was obtained. The second-level classifier was finally tested on the test data set.

GA based optimization evaluates the model's performance during training with various optimizers ("adamax", "adadelta", "adam", "adagrad"). The optimizer that gives the best performance was used for the model.

Similarly, during optimisation, the model training with various batch sizes (50,60,70) was conducted, and the batch size of 50 was selected for actual model creation.

The categorical cross-entropy was used during model training. For a classification problem, the evaluation metrics like Accuracy, Precision, Recall, F1-score, sensitivity, and Specificity are computed based on the confusion matrix C.

$$\text{Precision}=TP / (TP+FP) \quad (3)$$

$$\text{Recall}=TP / (TP+FN) \quad (4)$$

$$\text{F1-Score}=2*(\text{Precision}*\text{Recall})/(\text{Precision}+\text{Recall}) \quad (5)$$

$$\text{Sensitivity}=TP/(TP+FN) \quad (6)$$

$$\text{Specificity}=TN/(TN+FP) \quad (7)$$

The performance of an ensemble model depends on the individual performance of the base learners that complement each other.

Base classifiers used in the proposed approach display significant performance in an ensemble in comparison to the individual classifier performance.

In the proposed approach, the document feature matrix is input to an ensemble and processed subsequently through a convolution layer, max pooling, a fully connected layer, etc., to generate a classifier output. The output of the individual classifier was fused to generate the final ensemble output.

4.2. Results and Discussion

The optimal hyperparameter values using GA-based optimization for each of the CNNs in an ensemble are shown in Table 4 below. GA-based optimization of hyperparameters was done till the maximum accuracy was achieved or the number of generations was limited.

Figure 2 provides the training accuracy of the individual CNN models versus epochs. It is apparent that CNN model training accuracy increases as the number of iterations increases and remains constant after a certain threshold value of epochs.

Table 4. Optimal hyperparameter values for the cnn models in an ensemble

Layer	Structure	CNN1	CNN2	CNN3
First	Number of Filters Kernel Size Activation Dropout MaxPooling size	32 2 SeLU 0.2 2	32 2 SeLU 0.2 2	64 2 SeLU 0.2 2
Second	Number of Filters Kernel Size Activation Dropout MaxPooling size	32 2 eLU 0.2 2	64 2 eLU 0.2 2	64 2 eLU 0.2 2
Third(Dense)	Number of units Activation	512 eLU	512 eLU	512 eLU
Fourth(Dense)	Number of units Activation	5 softmax	5 softmax	5 softmax
Optimization		adamax	adamax	**adagrad**

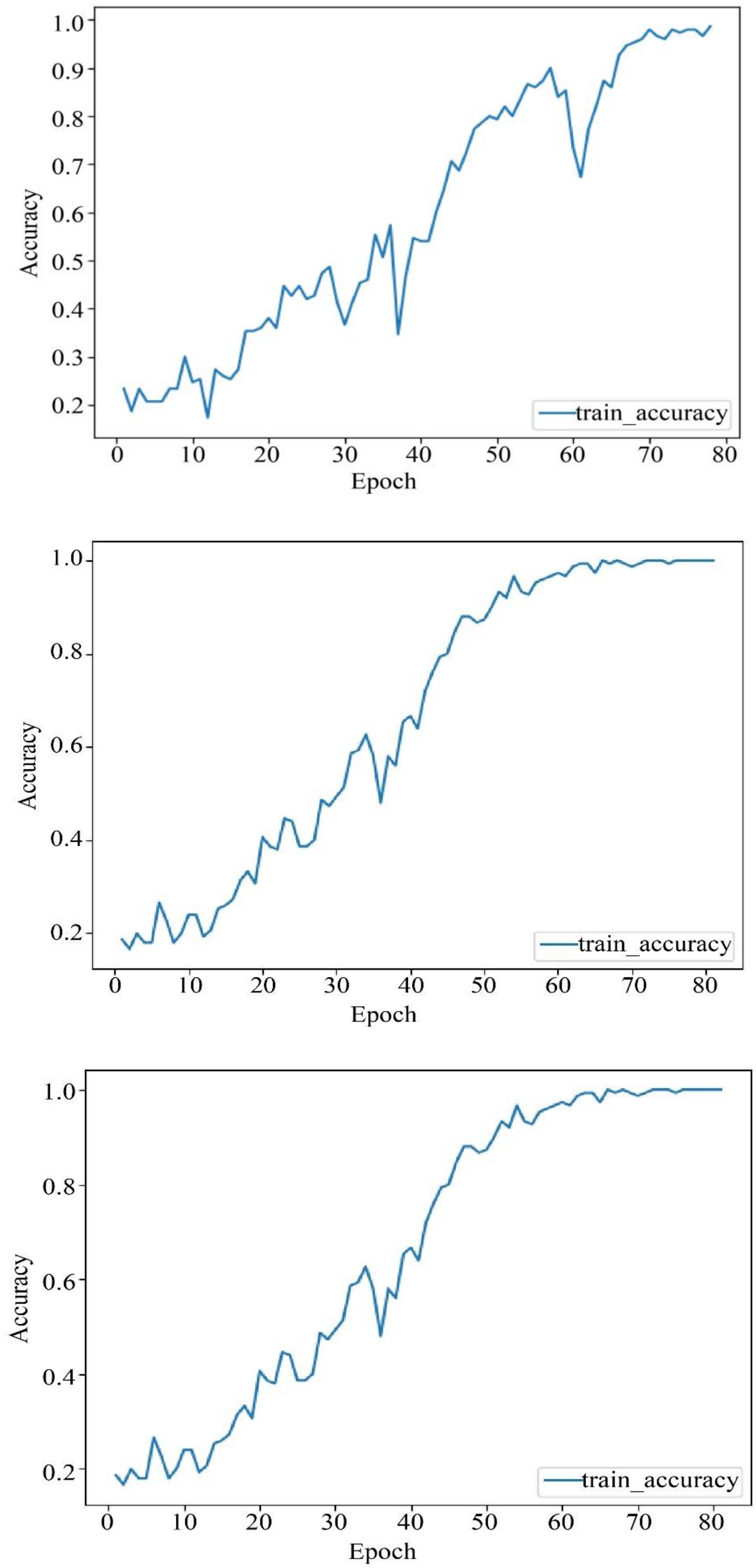

Fig. 2 CNNs model accuracy curves versus iterations obtained on GA based hyperparameter optimization of the three independent CNN base learners

Table 5. Classification performance of the baseline CNN models and the proposed ensemble approach

Model	Accuracy	Precision	Sensitivity	Specificity	F1-score
CNN1	0.77	0.821	0.77	0.77	0.7621
CNN2	0.8	0.86	0.8	0.8	0.804
CNN3	0.86	0.88	0.86	0.86	0.8636
Ensemble CNN	0.871	0.868	0.87	0.87	0.868
FuzzyEnsemble	0.92	0.89	0.87	0.78	0.8689

The proposed technique is compared with the baseline CNN model as well as the ensemble CNN, as mentioned in Table 5. It was found that the proposed approach has high accuracy and precision compared to the baseline/ensemble of CNN models.

Initially, sensitivity is high in comparison to specificity until they have the same value as accuracy. The proposed fuzzy ensemble model is compared with state-of-the-art models as shown in Table 6. The proposed model displays significant results.

Table 6. Performance metrics analysis of the proposed fuzzy ensemble model and state-of-the-art models

Model	Accuracy	Precision	Sensitivity	Specificity	F1-score
Logistic Regression	0.61	0.58	0.62	0.62	0.599333333
Decision tree	0.56	0.43	0.56	0.56	0.474282051
Support vector machine	0.561	0.682	0.44	0.44	0.534901961
Naive Bayes	0.57	0.586	0.56	0.56	0.572705061
Proposed Method	0.92	0.89	0.87	0.78	0.868998849

The results confirm that using a fuzzy ensemble of CNN with GA based hyperparameter optimization achieves high classification accuracy. The proposed method displays more significant results than the individual base classifiers/ensemble of CNNs on the dataset, justifying that the proposed approach's performance is enhanced using the advantage of fuzzy fusion of prediction of the base learners based on the assumption that all the models are not equally accurate in an ensemble to contribute to the prediction of the final output. And GA based optimization of hyperparameters. The hyperparameter optimization using GA optimizes the hyperparameter for CNN initialization and subsequent training. The classification accuracy of the trained CNN models is used as a weight during the fusion of the predictions of CNN models, giving more weightage to the baseline model with high individual classification accuracy in comparison to other baseline models. The increase in the classification accuracy of an ensemble confirms the effectiveness of the proposed approach of fuzzy weighted fusion of individual classifiers in an ensemble with GA based optimization of hyperparameters. During the experiment, 75 test queries each in the selected domain were issued to the GUI interface to retrieve personalized search results based on PWS(CNN with Fuzzy ensemble) and PWS(CNN with/without ensemble). Figure 3 compares the average precision of the recommended search results in selected domains using PWS(CNN with Fuzzy ensemble) and PWS(CNN with/without ensemble).

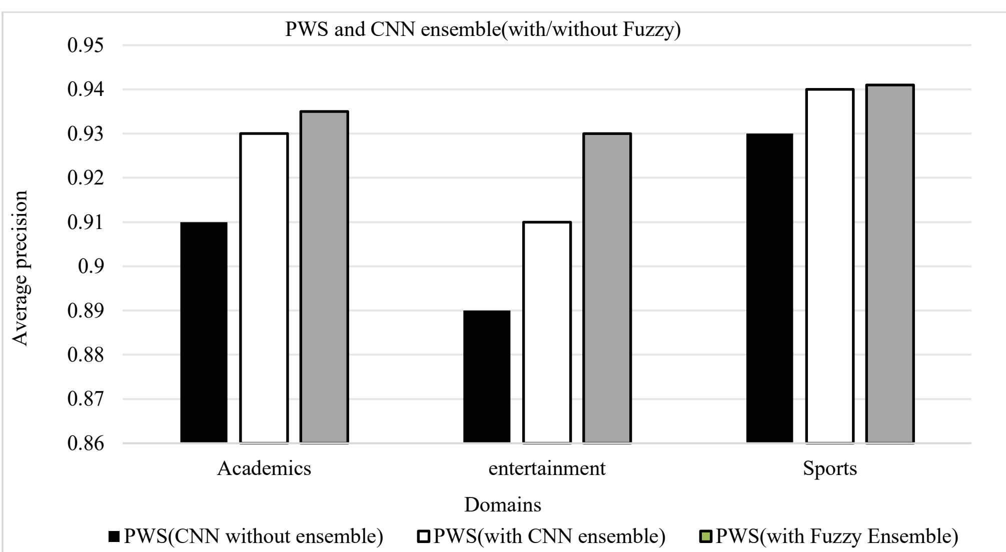

Fig. 3 Average precision versus domains for PWS using CNN (with/without Fuzzy ensemble)

The results were analyzed using a paired t-test for average precision with PWS (fuzzy ensemble of CNN) and PWS (CNN with/without ensemble) with 74 degrees of freedom (d.f.), as well as 24 df each for three selected categories (academics, entertainment, and sports). The t-test value for average precision PWS (CNN with fuzzy ensemble) versus PWS (CNN without/with ensemble) was 12.03 and 4.6429 for the whole sample, 8.93 and 3.81 for academics, 11.54 and 4.23 for entertainment, and 5.5 and 1.73 for sports categories. The paired t-test value is statistically significant and lies beyond the 95% confidence interval. Hence, it further confirms that the average precision of the recommended search results is improved significantly using PWS (CNN with fuzzy ensemble) because of the improved classification accuracy in comparison to other related methods.

5. Conclusion and Future Direction

In this paper, a novel approach is introduced using a fuzzy ensemble of CNN with GA based hyperparameter optimization for personalized web search. An ensemble of CNNs with different configurations of hyperparameters is used for training.

The training of CNN involves searching for the optimal value for hyperparameters that are computationally expensive; therefore, GA-based optimisation of hyperparameters is used because it does not have local optima. The experimental results displayed an increase in the classification accuracy using the proposed fuzzy ensemble of CNN with GA optimized hyperparameters.

The proposed approach improves the average precision during online processing compared to PWS (CNN with/without fuzzy ensemble). The training of deep learning models in an ensemble is computationally expensive, and therefore, the scalability of the proposed method on big data is a big challenge. This challenge can be addressed in the future by using the feature selection method and Big Data technology like Hadoop.

Data Availability

The datasets generated during and/or analysed during the current study are available in the Kaggle repository, [https://www.kaggle.com/datasets/sunilthite/text-document-classification-dataset.]

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