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# Intelligent Web Search Recommender System: An Application of Ensemble of Convolution Neural Network for Deep Semantic Content Analysis of Web Documents

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**Abstract**

Web Information retrieval is widely used for retrieving web documents relevant to the user search query. Search engines retrieve huge collection of web documents for a given search query and an information overload problem arises for the web user. Web page recommender systems are widely used to deal with the information overload problem. Quality of the web page recommendations for a given search query depends heavily on the document feature representation. In this research a novel method is explained for Intelligent web search based on deep semantic content analysis of clicked web documents using an ensemble of convolution neural network. Deep learning model Convolution neural network has been used in the research for feature generation and it effectively represents the text characterization for classification. The optimized web document feature vector is generated using the ensemble of CNN is finally averaged at the output layer for clustering. The resulting clusters of optimal web documents optimized feature vector therefore groups semantic similar web documents in a given cluster for web page recommendations during web search. Experiment results confirm the improvement in average precision to 93% across all selected domains that shows the relevant web documents are increased in the recommendations based on clusters of web document optimal feature vectors generated using ensemble of CNN. Thus, the proposed system performs the Intelligent web search recommendations based on the deep semantic deep content analysis of web documents using an ensemble of CNN.

*Keywords:* Artificial Neural Network, Intelligent Web Search, Convolution Neural Network, Clustering, Ensemble Learning, Fully Connected Neural Network, Word Embeddings, Web Applications

## 1. Introduction

Recommender systems overcome the information overload problem on the web. It provides relevant information to the user based on user's interest profile and prevents the user 's effort to sift through the large volume of web information. Recommender systems are applied for various web applications. Web page recommender system has been used to retrieve the web document relevant to the user's search query and overcomes the information overload problem [1], [2], [3], [4].

The building of high-quality web recommender system in order to provide the personalized recommendations is a big challenge. Now a days recommender system faced with the scalability problem when input data to the recommender system is large. Feature reduction and clustering techniques are used to find the similar recommendations in clusters instead of the whole database. Content based recommender systems are widely used for personalized web services. ANN is widely used for pattern recognition in data. FNN is the ANN that use nonlinear transformation function to learn the complex pattern in the data. CNN has been widely used for feature learning. CNN model for text classification shows significant performance in comparison to other machine learning techniques [5].

Despite the recent advances in the recommender systems, there is still the scope of improvement in the quality of web recommender systems. It is found in the research that deep learning model generates high performance web recommender systems. Ensemble learning is another research area that combines the output of two or more classification model and displays the significant classification accuracy. Ensemble learning using multiple classifiers

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are widely used to enhance the classification accuracy of the classifiers. It is found that CNN is sensitive to its hyperparameters like number of filters, filter size and depth of the neural network etc. Therefore, the ensemble of CNN can be created using multiple CNN with different configuration of its hyperparameters as base classifiers. Ensemble classifier used for text representation shows the significant performance in text classification with an accuracy of 98.5% based on feature extraction techniques (TF-IDF) [6].

In this paper an architecture for Intelligent web search using an ensemble of CNN (combining the merits of deep learning model and ensemble learning model) for content-based web page recommender system is proposed. An ensemble of CNN classifiers is used for deep semantic content analysis of clicked web document and generates the optimal web document feature representation. The quality of the web page recommendation based on a given search query depends on the web document feature representation. Initially, web documents are preprocessed using NLP and mapped to a matrix using word embedding Word2Vec. During the training of CNN for web document feature vector generation, its weights are optimized based on loss function that depends on the quality of the clusters with respect to web document feature vector assigned to the clusters.

The training of ensemble of CNN continues till the loss function is minimized therefore generates the optimal web document feature vector for effective clustering. Thus, the application of deep learning algorithm CNN in web document content mining generates the optimized web document feature vectors for clustering. The clustering of these optimized web document feature vector groups the semantic similar web documents for recommendations catering to the user' information need and overcome the information overload problem for Intelligent web search. Experiment was done to evaluate the performance of an ensemble of CNN for web document feature vector generation. The experiment observes more user's clicks to recommended search results that further confirms the quality of clusters is improved based on web document feature vector generated using an ensemble of CNN classifiers. Furthermore, these web document feature vector when used for clustering brings semantically similar web document in a given cluster and therefore Intelligent web document recommendations using cluster of Ensemble-CNN based optimal feature vectors satisfy the user information need effectively.

## 2. Related work

Recommender model based on linear programming was used for quality decisions but it is difficult to execute the model on real large-scale applications. Fuzzy logic used the rules in recommender system for the complex problems but the model is not scalable. K-nearest neighbors (KNN) is simple to implement and used to detect emotion from the changing electric signals collected from the sensors. The model shows accuracy in classification. An Artificial neural network has been used for learning and generating the data pattern accurately [7], [8], [9], [10], [11].

Firefly algorithm (FA) was used in recommender system and results showed the increased efficiency. FA cannot be applied to other optimization methods. Beetle Antennae Search (BAS) had been used in the recommender system and displays significant performance. The search accuracy of BAS algorithm was low and exploration scope is limited. A recommender system was developed based on HashMap for personalized advertisements but the model has high time complexity. Hybrid multicriteria recommender system was developed using GA but the model lacks personalization [12], [13], [14], [15].

Recommender systems for online shopping was implemented using random forest and convolution neural networks. Model showed significant performance for product recommendation. Recommender system was developed using trust concept but the model has limited applications. Web movie recommender system was developed using Singular Value Decomposition (SVD), But the system had the sparsity and low accuracy problem. Reinforcement learning was used in the dynamic goods recommendation system. FNN was used in movie recommendation system [16], [17], [18], [19].

A movie recommender system using collaborative filtering and heterogeneous information was proposed but the model was complex. Ensemble learning model was used to combine the output of two or models for final classification and displayed better performance. The overfitting on the data was avoided in recommender systems. Semantic based similarity model was used in the software environment. Content-based filtering was used for recommender system and the sparsity issue was solved. It is found deep learning-based recommender systems along with feature reduction had been applied for recommender systems. Deep learning model in recommender systems has shown high performance accuracy [20], [21], [22], [23], [24], [25].

Novel ensemble method for multilingual text classification was proposed and results confirmed the significant performance. The deep learning models uses complex non-linear transformation in feature learning and displays significant performance. Ensemble model is implemented based on training of several classifiers and enhances the classification accuracy based on combining method of predictions of baseline classifiers. Deep ensemble learning models is widely used as it combines the merit of both the deep learning models as well as the ensemble learning. CNN is one such deep learning model that displayed significant performance. The training of ensemble model using deep learning neural network is costly because of huge number of hyper parameters of the baseline deep learning models in an ensemble. In this paper homogeneous ensemble deep learning model is used as they are easier to understand and apply where the diversity in the ensemble model is introduced based on changing the hyper parameters of the same baseline model. Thus, the number of hyperparameters used for training in an ensemble of diverse deep learning model is reduced using the different structure of the same baseline models by changing few hyper-parameters values. Deep learning-based ensemble model was used for heart disease detection based on ECG [26], [27], [28].

It was found in the research that CNN has been used as the feature extractor for many applications as well as for clustering. CNN and support vector machine had been used for various applications like image classification as well as Arabic handwritten recognition and the high accuracy of 90% is obtained. An ensemble of different classifiers was used for medical document classification and twitter text documents. Four different CNNs were used for sentence level sentiment classification. CNN was used for sentiment classification of short texts as well as using character encoding. Semi-Supervised CNN was used for learning embedding of small text regions [29], [30], [31], [32], [33], [34], [35], [36], [37], [38].

Word embeddings like Word2vec, GloVe and fastText are the pretrained vector that map the document to dense feature vector of low dimensionality. Word embedding generates word vector trained based on the document corpus. Word embedding training requires computational time and preprocessing time in comparison to the pretrained vector [39], [40], [41], [42], [43].

Due to paucity of labeled data, unsupervised machine learning algorithm like k-means has been widely used for clustering due its simplicity. The objective of k-means is to minimize the distance of the data points from centroid from within the cluster in comparison to inter cluster distance. k-means clustering based on k-fold uses a fold for initializing cluster center and whereas data points in the remaining k-1 folds evaluates the method based on assigning the data points to the closest cluster centroids. The feature vector generated using an ensemble of CNN model are clustered using k-means and the clusters are optimized based on the distance between feature vector $x_n$ assigned to the cluster and $\mu_c$ in eq(1).

$$J_{KM} = \sum_n \sum_c r_{nc} \|x_n - \mu_c\|^2 \quad (1)$$

$c \in 1..C, x \in R^n, \mu_c$ is the cluster centroid and $r_{nc}$ is defined as an indicator where data point n is assigned to a given cluster c (1) or not(0). The cross entropy loss L is computed based on the ensemble web document feature vectors $f(x_i, w)$ and its assigned cluster mean $\mathcal{y}_c$ as given in eq(2). The optimized cluster mean is computed and represented by $\mathcal{y}_c$ as given in eq (3).

$$\min_w \frac{1}{N} \sum_{i=1}^{N} L(f(x_i, w), \mathcal{y}_i) \quad (2)$$

$$\mathcal{y}_c = \frac{\sum_n r_{nc} * x_n}{\sum_n r_{nc}} c = 1..C,\ x \in R^n, r_{nc} \in \{0,1\} \quad (3)$$

$f(x_i, w)$is the CNN function that generates the feature vector, $\mathcal{y}_c$is the cluster centroid, given input data $x_i$and weights w. The loss function is minimized by updating the weights in an ensemble of CNNs model using stochastic gradient descent (SGD) backpropagation algorithm. [44],[45], [46].

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## 3. Proposed Methodology

In this paper a novel method is proposed for Intelligent Web Search based on deep semantic analysis of web documents using an ensemble of CNN. Deep semantic content analysis of web documents using ensemble of CNN generates optimized web document feature vector for effective classification. In deep semantic content analysis, the multiple CNNs generates the multiple document feature vector which is therefore averaged at the final output of the ensemble. The flowchart for the ensemble of three different CNN with different configuration of its hyperparameters for document feature generation is shown in figure 1 below.

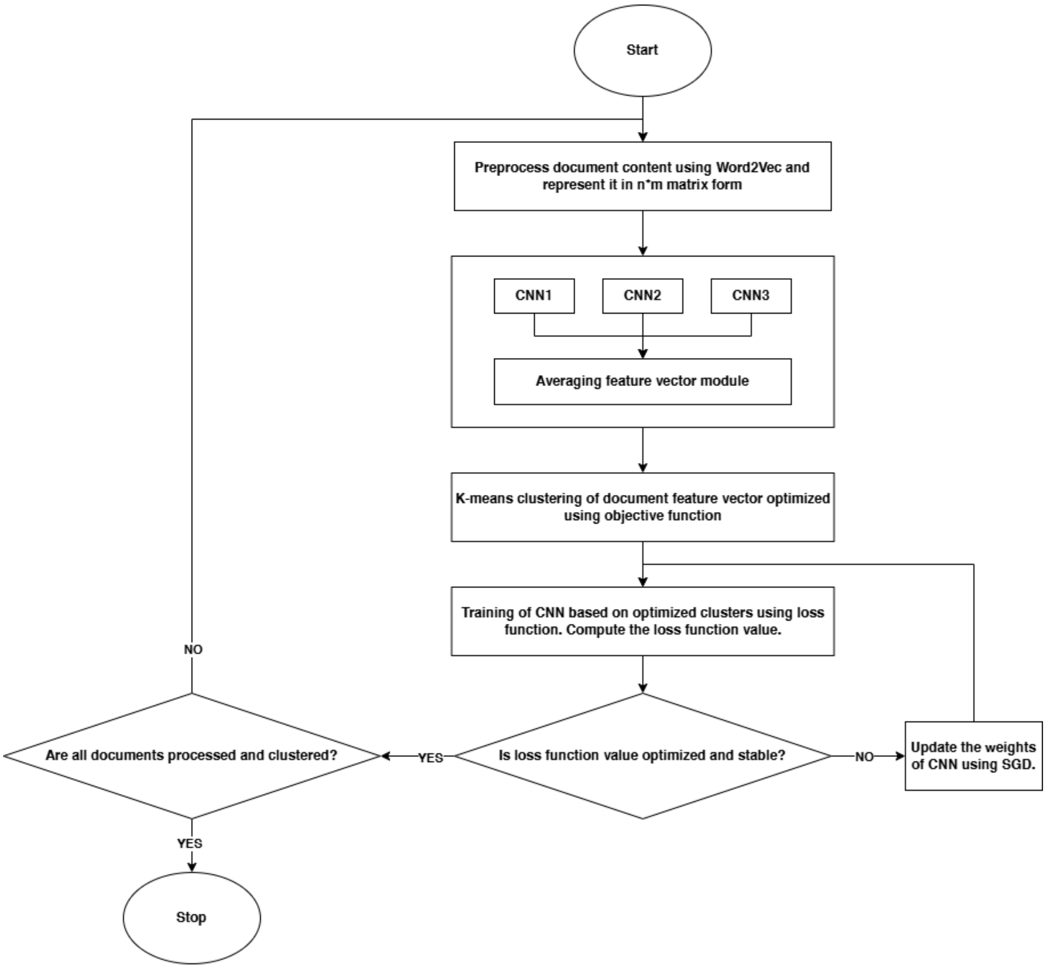


**Figure 1.** Displays the steps used for deep semantic content analysis of web documents using ensemble of CNN.

The baseline models CNNs hyperparameters are modified in the specified range to determine the optimal hyperparameters for CNN1, CNN2 and CNN3 therefore the ensemble of CNN1, CNN2 and CNN3 with different filter size, number of filters, batch size and epochs are selected for the generation of text feature vector. The document feature vectors from CNNs are averaged to represent the web document content used for clustering. The resulting clusters of web documents are optimized using eq (1).

The training of the CNN model is based on the loss function that measure the quality of optimal document feature vectors assigned to the clusters. The trained ensemble of CNN is evaluated on the test data set. The feature vectors from different CNNs in the ensemble are averaged to generate the semantic document feature vector. These web documents vectors are clustered for recommendations during online web search.

An algorithm is proposed for Intelligent Web search that can be used as a recommender system in real life for semantic personalized web search. The proposed algorithm initially uses Google API to retrieve the search results. The use's response to search results is captured and stored for deep web mining using the proposed approach in the offline processing. During online processing, the user's search behavior is captured to generate the user profile vector for the

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selection of cluster in the mined database. The selected cluster that groups the semantic similar web documents for recommendations catering to the user' information need for Intelligent web search. Thus, the application of deep learning algorithm CNN in web document content mining generates the optimized web document feature vectors. The clustering of these optimized web document feature vector that groups the semantic similar web documents for recommendations catering to the user' information need for Intelligent web search. Thus, the proposed approach can be implemented as web search recommender system for personalized web search. The algorithm used in the proposed Intelligent Web Search has two parts: offline and online for implementing the proposed method. The steps used for offline processing is as follows in Algorithm 1.

**Algorithm 1. Offline Processing: Procedure Ensemble of CNN for deep semantic content analysis of web documents.**

**Offline processing**-Ensemble of CNN for deep semantic content analysis of web documents.

**Input**: Web documents

**Output**: Semantic Document feature vector.

1. The web documents are preprocessed and transformed to a matrix of size u*v using Word2Vec embedding where u is the number of distinct words and v is the Word2Vec embedding size.
2. Document word matrix is input to the ensemble of three CNN network and the document semantic vector from each CNN is averaged at the output.
3. **Repeat step 2 till all the web document feature vectors are generated.**
4. The document feature vectors generated using ensemble are clustered using k-means optimized using objective function eq (1).
5. The loss function is computed based on document vectors assigned to a given cluster and its cluster centroids eq (2).
6. The training of ensemble of CNN is done using SGD till the loss function value is minimized to certain threshold value.
7. The trained ensemble of CNN model generates the optimal document feature vectors averaged at the output.
8. Thus, these optimal web document feature vectors are clustered for use in online processing as given in algorithm 2 (online processing).

In offline processing, web document d with u words is represented as a matrix where each word is mapped to a vector of a given dimensionality using Word2vec pretrained vector. Word2Vec uses neural network for training on web document corpus in a given domain. The trained Word2Vec maps the words of the document content to vectors such that words with the similar meaning are mapped to similar vector. Thus, the web document content vector of size u is mapped to matrix of size u*v where each word is mapped to a vector of fixed v using trained Word2Vec model. The resulting web document matrix is processed through a convolutional layer, pooling layer, and normalization layer, ultimately generating the output feature vector.

Training of CNN ensemble is done on web document matrix representation of size u*v. The feature vectors generated using individual CNNs in the ensemble are averaged at the output layer. This resulting document feature vectors are clustered. The loss function is computed based on the distance between the document feature vector and cluster centroid assigned to it. The training of ensemble continues till the loss function is optimized.

k-means clustering is a scalable model with good precision rate therefore used for clustering the large volume of web document feature vectors. The clusters optimized using objective function minimizes the dissimilarity within the cluster data points and increase the inter cluster dissimilarity. Once all the feature vectors are assigned to the clusters, the clusters centroids are updated to compute the loss function. The training of CNN continues till the loss function value is reduced to the desired tolerance or till the specific number of epochs is completed.

These clusters of web documents features are optimized during training of ensemble of CNN model. Once the training of CNN model is completed, an ensemble of CNN models optimized based on loss function generates the web document vector such that web document that are semantic similar are represented by similar web document vector. Therefore, the optimized web document vectors generated using an ensemble of CNN models groups semantic similar web document using clustering algorithm. These clusters of semantic similar web documents are used for Intelligent web search during online processing. The steps of algorithm in online processing for web page recommendations is given below in algorithm 2.

**Algorithm 2. Online Processing: Procedure Ensemble of CNN for deep semantic content analysis of web documents.**

**Online processing**-Ensemble of CNN for deep semantic content analysis of web documents.

**Input:** Clusters of web documents

**Output**: Web page recommendations for PWS.

1. The clusters mean is computed for each cluster based on optimal web document optimal feature vectors present in clusters.
2. The web search query similarity with cluster means is computed for selecting the most similar cluster.
3. The web documents in the selected cluster are used for recommendations during web search.
4. **Repeat the following on request of next search result page:**
5. The user's selected recommended web documents are captured to generate the current user search session.
6. The user search session vector is computed based on the summation of the clicked web documents optimal feature vector.
7. The cluster mean similarity with user search session vector is computed for the selection of the most similar cluster.
8. The selected cluster generates the web page recommendations.
9. Go to step 4

During online processing, initially the web search query similarity with cluster centroids is computed to select the cluster for web documents recommendations. The user search session vector is computed based on the user's clicked documents vector. Thus, the recommendations of web documents based on the cluster selected using user search session vector persists till the user search session is terminated.

## 4. Experiment

The proposed model was performed on the text document data set downloaded from the Kaggle https://www.kaggle.com/datasets/sunilthite/text-document-classification-dataset. The dataset contains 2225 text data in five categories namely politics, sport, tech, entertainment and business. The experiments were performed on core i7 3.80 GHz, 32-GB RAM with tensorflow in the python environment. NLTK library was used to represents the web documents as the list of words after stopword removal and delimiter removal. Gensim package was used for Word2Vec model generation. Word2Vec was trained on the web document corpus. The trained Word2Vec embedding mapped the document word vector to matrix where each word was mapped to a vector of fixed length. An ensemble of three CNN model was created. CNN is sensitive to its hyperparameters therefore three CNN models were created with different configuration of filter size, number of filters. Research had already been done using CNN and it was found that hyperparameters optimization of the CNNs is time expensive and therefore it was varied in the limited range that also shows satisfactory performance of CNNs in previous research similar to the proposed. Therefore, CNNs model hyperparameters like number of filters were varied in the range [32] to [64], filter region size in [2,5], drop out in [0.1,0.5] and epochs in [5,10]. The performance of an ensemble of CNN models was optimal (minimum loss function) with the following parameters number of filters=64, region size 3(CNN1),4(CNN2) and 5(CNN3), dropout=0.5, batch size=64 and epochs=10. The variable length feature vector/maps were generated on applying filters of variable region size on document matrix of the size u*32 where 32 is the embedding size. Then next pooling layer that takes the maximum value from the specific region of document matrix and generates the feature vector of a given length. This feature vector was processed using FNN therefore generated the one-dimensional feature vector after nonlinear transformation RELU (rectified linear unit)) was performed at the output layer.

Thus, the ensemble of convolution neural network of different configuration generates the output feature vector that was averaged to represent the final document feature vector. The final document feature vectors were used in k-means clustering.

The training of CNN ensemble was performed using SGD for optimizing the document feature vectors. Thus, during training of CNN, filter weights were changed based on optimization of loss function. The loss function versus iterations during training of ensemble CNN is shown in figure 2 below.

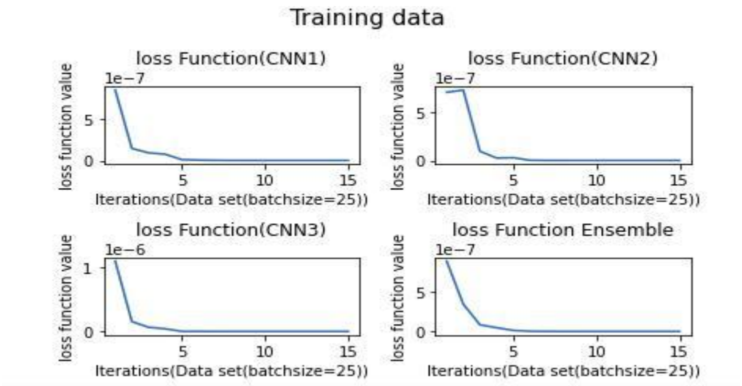


**Figure 2.** Shows the loss function versus iterations during training of CNN1, CNN2, CNN3 and aggregate loss function of ensemble of CNNs.

In figure 2 it is observed that loss function value decreases as the number of iterations increases during the training of individual CNNs. Thus, loss function value of the ensemble CNNs also displays the same pattern. Loss function is of order 1e-7 initially for CNN1, CNN2 and ensemble and 1e-6 initially for CNN3. This loss function gradually decreases to zero. Thus, the trained Ensemble CNN was then applied on the test web document feature vector. The loss function on the test data set is shown in figure 3 below.

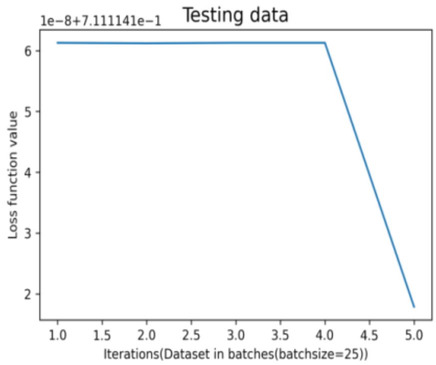


**Figure 3**. Displays the loss function versus iteration of the trained CNN on the test data set.

Figure 3 shows the loss function decreases steeply when the trained CNN was implemented on test web document data set to generate the optimal document feature vectors for clustering. The proposed method is novel and was compared with other state of art models such as Decision tree, Logistic regression, Support vector machine and Naive Bayes and CNN on the same data set. During the training of the models, the data set is split to 75% training data set, 25% test data set. In classification models, confusion matrix was used to compute various metrics that measure the accuracy of the models. Metrics used in this paper are as follows.

$$\text{Accuracy} = (TP+TN)/(TP+FP+TN+FN) \quad (4)$$

$$\text{Recall}=\text{Sensitivity}=TP/(TP+FN) \quad (5)$$

$$\text{Specificity}=TN/(TN+FP) \quad (6)$$

$$\text{Precision}=TP/(TP+FP) \quad (7)$$

$$\text{F-Score}=2*\text{Precision}*\text{Recall}/(\text{Precision} + \text{Recall}) \quad (8)$$

The comparison of the training as well as testing analysis of the proposed method with the other state of art models is given as follows in table 1.

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**Table 1.** Comparative analysis of performance metrics of proposed ensemble model along with other state of art models.

| Model | Accuracy | Precision | Sensitivity | Specificity | F1-score |
|---|---|---|---|---|---|
| Logistic Regression | 0.610 | 0.580 | 0.620 | 0.620 | 0.599333333 |
| Decision tree | 0.481 | 0.430 | 0.540 | 0.540 | 0.478762887 |
| Support vector machine | 0.561 | 0.682 | 0.440 | 0.440 | 0.534901961 |
| Naive Bayes | 0.570 | 0.586 | 0.560 | 0.560 | 0.572705061 |
| CNN | 0.750 | 0.750 | 0.745 | 0.745 | 0.747491639 |
| Proposed Method | 0.871 | 0.868 | 0.870 | 0.870 | 0.868998849 |

Result confirms that the proposed ensemble method has the high accuracy, sensitivity and specificity in comparison to CNN and other state of art models thus the classifier with high accuracy, sensitivity and specificity implies that majority of the times predicted class of the pattern is same as the actual class.

### 4.1. Result Analysis of Web Recommender Using Web Document Feature Vector Based on Ensemble Model

The feature vector data set from the proposed ensemble CNN was partitioned to k- fold where first fold was used for cluster center initialization and the remaining k-1 fold feature vectors were assigned to the nearest cluster centroid with maximum similarity measure. The decrease in the loss function implies that clusters quality is improved drastically based on test documents optimal feature vector present in the given cluster and the loss function is minimized as the distance between optimal document feature vector and cluster centroids is minimized. These clusters of web documents optimal feature vector group semantically similar web documents for recommendations during web search.

The performance of the Personalized web search using the proposed approach was evaluated based on the user's response to the recommended documents. The recommended documents marked with check boxes were displayed on the GUI interface. The use's selection to the recommended documents were captured through check boxes and further used for computing the average precision of the recommended search results. The students from the author institution were selected for evaluating the effectiveness of the recommender system based on the proposed system. 10 students each having knowledge in the selected domains were used for the evaluation of the proposed system. 25 search queries were issued by the group of 10 students in a given domain and the average precision of the 25 search queries in a given domain was calculated to evaluate the effectiveness of the recommender system based on the proposed system. The performance of clusters of optimal web document feature vector was determined from the average precision of the recommended web documents as shown in figure 4.

Figure 4 confirms that average precision is improved in the given domain based on the clusters of document optimal feature vector using PWS (with ensemble) in comparison to PWS (without ensemble). [4] The experiment results confirm that the number of relevant documents is increased in the recommended search results. Thus, the use of ensemble of CNN generates the clusters of semantically similar web documents feature vectors for Intelligent web search recommendations.

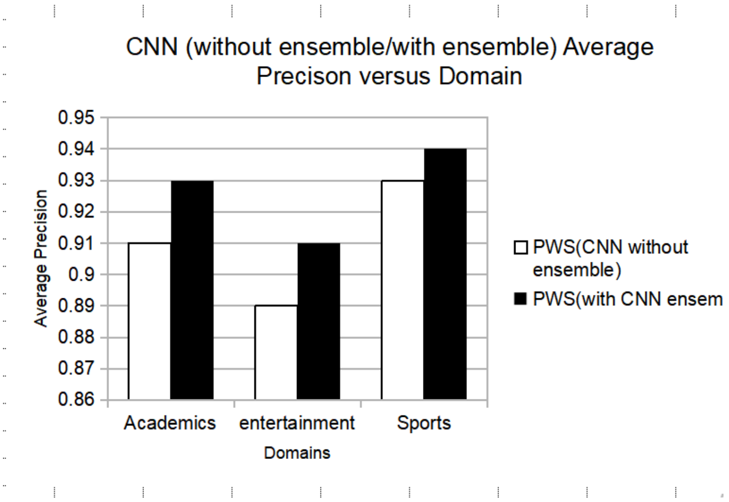


**Figure 4.** Displays the average precision of PWS using CNN (with/without ensemble)

### 5. Conclusion and Future work

In this paper an ensemble of CNN classifiers is used for generating the optimal web document feature vectors. Ensemble of three CNN is used based on varying the values of selected hyperparameters. Ensemble of CNN is applied on preprocessed web documents. The web document feature vector generated from each CNN is finally averaged and are clustered using k-means. Experiment results confirm that ensemble of CNN is effective in generating the web document average feature vector for clustering that brings semantic similar web document together for recommendation during web search. Thus, the Intelligent web search using CNN based optimal document feature vectors generates effective recommendations and displays significant results in comparison to the other state -of- art models. The proposed approach is not scalable to big data on the web. Therefore, the modification of the proposed approach is required for processing the big web document data and generates web documents recommendation for Intelligent web search. For future work, the proposed approach can be made scalable by implementing it in distributed and parallel computing framework like Hadoop.

### 6. Declarations

#### 6.1. Author Contributions

Conceptualization: S.C.; Methodology: S.C.; Software S.C.; Validation: S.C.; Formal Analysis: S.C.; Investigation: S.C.; Resources: S.C.; Data Curation: S.C.; Writing Original Draft Preparation: S.C.; Writing Review and Editing: S.C.; Visualization: S.C.; The authors have read and agreed to the published version of the manuscript.

#### 6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

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The authors received no financial support for the research, authorship, and/or publication of this article.

#### 6.4. Institutional Review Board Statement

Not applicable.

#### 6.5. Informed Consent Statement

Not applicable.

#### 6.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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