Adaptive Graph Convolutional Network for the Document Prediction employing Dollmaker Optimization Algorithm

T. Elavarasi[1] and Dr.R.Nagarajan[2]

[1]Research scholar,Department of computer and information science, Annamalai University, Email: arasithirugnanam@gmail.com
[2]Assistant Professor/Programmer, Department of computer and information science, Annamalai University, Email: rathinanagarajan@gmail.com

KEYWORDS
Document Prediction; Adaptive Graph Convolutional Network; Dollmaker Optimization Algorithm; Difference of Gaussian.

ABSTRACT
Document prediction is the application of advanced deep learning models in the analysis and prediction of the content of documents. Thus, it effectively improves text generation, information retrieval, and automatic summarization by changing the ways relating to textual data completely. This field is particularly challenging because maintaining high prediction accuracy requires efficient computing and scaling. Hence, this paper performs the document prediction using advanced deep learning-oriented optimization methodology. The data is first collected from online sources that consist of a group of documents together with their corresponding categories. The pre-processing of this collected data is next accomplished using the stop word removal, invalid character removal, and sentence segmentation approaches. The features are then extracted from these pre-processed data employing the Difference of Gaussian (DoG) method. The final prediction stage is done by the novel Adaptive Graph Convolutional Network (AGCN), in which the parameters are tuned by the well performing optimization algorithm known as Dollmaker Optimization Algorithm (DOA) with the consideration of error minimization as the fitness function. The findings demonstrated the superiority of the proposed model when it is compared with distinct conventional models.The proposed AGCN-DOA for the document prediction model in terms of prediction accuracy, MSE, MAE, MAPE, and RMSE is 11.18%, 94.73%, 31.71%, 47.73%, and 77.03% better than the considered existing methods respectively..

1. Introduction

As everyone know, the rise of technology and increased access to the Internet has resulted in a dramatic increase of documents especially in business, health care, education and legal practice and other areas [1]. With the increase of information, there is a need for efficient ways of handling data and accessing appropriate information. This has given rise to document prediction, which is the ability to forecast the importance or category of a document based on any text content it possesses, as an important feature. Most of the methods employed are traditional in nature, using either rule based approach or shallow learning models that are incapable of dealing with the depth and diversity of textual material [2].

More specifically, Deep learning – a branch of machine learning, also presents viable alternatives to these issues. With the use of Neural Networks (NNs) especially the complex ones, it is possible to comprehend the complicated textures and relations of wordings that even the most sophisticated algorithms would fail to process [3]. This is very useful especially in document predictions in which the language used and its context may affect the predictions made greatly. Optimization is central to the improvements of performance in deep learning models. Strategies such as transfer learning and fine- tuning of available models allow to increase performance on particular document prediction tasks, even with small amount of labelled data, using already available resources [4].

Embedding deep learning optimization techniques within the document prediction systems improves their efficiency and effectiveness in searching for information. In the case of modern organizations that seek to be data driven, the art of predicting the relevance of a content in a short span of time and with extreme accuracy becomes a key issue [5]. This not only helps to conserve time and eliminate waste but also facilitates a more comprehensive exploration, thereby fostering innovations and effectiveness in different sectors. Looking into this aspect, the use of deep learning and optimization for enhancing document prediction is a great leap in leveraging information who would have otherwise needed it through different mechanisms.

The paper contribution is as below.

- To perform the document prediction using advanced deep learning-oriented optimization methodology.
- To pre-process the data using the stop word removal, invalid character removal, and sentence segmentation approaches and to extract the features employing the DoG method.
- To do the prediction by the novel AGCN, in which the parameters are tuned by the well performing optimization algorithm known as DOA with the consideration of error minimization as the fitness function.

The paper organization is as follows. Section 1 is the introduction regarding the document prediction. Section 2 is literature survey. Section 3 is proposed methodology with proposed model, data collection, pre-processing, feature extraction by DoG, prediction by novel AGCN, and DOA. Section 4 is results and analysis. Section 5 is conclusion.

1.1 Motivation

There is a paradigm shift in data analysis and information retrieval, thanks to the innovative techniques of document prediction basing on deep leaning optimization. Digital documents are on the rise and traditional systems cannot manage the complexity and the diversity of text based content. Neural networks related deep learning methods are powerful in identifying complex structures in a vast amount of data, which in turn facilitates the prediction of a given document and its assigned category more effectively. Enhancements in model performance can also be achieved through advanced optimization algorithms in a way that the predictions are not only quick but also accurate. This can be beneficial to many business industries including decision making in the law and finance sectors to health care and even education. In other words, organizations are able to draw great benefits from their data which fosters efficiency and promotes creativity as deep learning in document prediction becomes mainstream. The more one make progress in this area, the greater the extent to which it will be possible to improve the access to and use of information, which is why this area will be the subject of much attention in coming years in terms of research and application.

2. Related Work

In this document, a novel approach for predicting topics in writings in the Urdu language has been furnished, which was less supervised and provided much more useful knowledge from the given texts [6]. The key phrases were organized based on the keyword scores and reorganized based on the order they occur in the document. Last but not the least, the approach in this study determined top keyphrases in terms of topical importance.

A multi-modal prediction model called MultiSChuBERT was devised [7]. This research made three substantive contributions to the present-day SDQP. To begin with, the potential outcomes generated by the hybridization of visual and textual embeddings were demonstrated. Further, it was shown that using a gradual-unfreezing strategy mitigated its over-fitting problem and improved the quality of the results. Finally, it was demonstrated that the advantage of having multi-modality was still present. Similar improvements were observed with the task of predicting accept/reject on PeerRead.

This paper looked at the possibility of an AI insinuated mechanization of stock price prediction which might be the ultimate game changer to the operations of the financial sector and the advantages that such a system would bring to all parties concerned [8].

The use of GCNs was studied in text classification with multiple labels [9]. It proposed the development of plain text graphs that combined the structure of documents with their similarity, label associations, and similarity between the labels. The GCN was able to assign class label to the documents, learn their relational structure and the document contents in the TF-IDF sense. Unlike conventional machine learning techniques that assumed labels were independent, this technique incorporated the learning of dependencies between labels.

The focal point of this document was using a blind method that was able to quantify the image of the document regardless of its archival status, as this was often the case in practice [10]. It was cut into a number of small sections referred to as patches from the document image. These extracted patches gone through a patch selection process whereby they were sorted based on the amount of foreground content the patches hold. For each patch that was preserved, a bag of visual words that was developed on k-means clustering was used to determine the patch quality by looking at the bags of visual words and assigning each patch to a cluster. The results produced by the developed technique proved the validity of the DIQA approach. It became natural to consider creating efficient instruments for the process of document image forgery detection and management.

The authors of paper [11] present an original approach that was intended to forecast voting outcomes of the Korean Monetary Policy Committee. Text from previous study about monetary policy decisions was fed to classification models to forecast the sentence sentiment. Lastly document sentiment was obtained by employing an aggregation of sentence sentiments and vote outcome was forecasted using such sentiment.

The Multi-Modal Layout-Aware Relation Prediction was an innovative scheme [12]. One aspect of this method was its simple but very effective task definition aimed at predicting the ordering relation among the textual instances. The performance showed that this method was capable of achieving a new best performance level.

A new semantic model was proposed to portray crime where a Criminal Action Graph (CAG) was developed by linking together various criminal actions in two separate temporal planes [13]. Using CAG, Legal Charge Prediction was also outlined using Graph Convolutional Network. The findings demonstrated the usefulness of this model in encoding and exploiting the semantic content of legal judgment documents.

This research made a suggestion concerning an ACNNDS that was an acronym for Attentive Convolutional Neural Networks representing Document and Sentence for the purpose of rating prediction [14]. Not all users, raised the same reviews, as the importance of sentences and words in her/his review varies. In order to address this issue, a sentence-level and document-level attention mechanisms were developed in order to identify the important sentences and words in the reviews. The results of the experiments showed that the ACNNDS enhanced the recommendation performance, which was much higher than the performance of the alternative methods.

The construction of a Document Analysis Deep Regression Model (DADRM) was a recent turn in the quest to mine information [15]. A comparative study was performed in order to check the usefulness of the framework concerning prediction of ICO success in funding amount. Empirical evidence demonstrated that model with inserted text content could enhance prediction accuracy. However, thanks to this method, itdecreased the asymmetric information problem. Moreover, this research provided that the content of the business text and the design of the text in turn influenced the investors' decisions.

2.1 Problem statement

Therapid increase in digital documentation brings an enormous challenge in managing and retrieving the necessary information with ease. Most of the old techniques developed for classifying and predicting documents tend to be inadequate due to the complexity, plurality, and volume of modern datasets over the conventional ones. This makes it difficult for the organizations to filter out unnecessary and important documents which in turn leads to wastage of labor, time and resources. The problem is even worse because of the simple algorithms which conventionally do not grasp the text's inner meaning and relationships of the data presented in such data. Because of this, it is obvious that more sophisticated methods that incorporate deep learning to improve the accuracy of predicting documents are inevitable for the survival of this niche. By pooling strategies focused on optimization based on deep learning, it becomes possible to create a dependable architecture that will make it possible to process significant amounts of text, identify complex relations, and make in time, accurate, context-based assessments. This will not only enhance the methods employed in seeking and retrieving information but it will also lead to the discovery of more ways of mechanization and generating useful information in other fields.

3. Proposed Methodology

3.1 Proposed Model

The proposed document prediction model includes various phases such as data collection, pre-processing, feature extraction, and prediction.The group of documents along with their corresponding categories on the online source is first accumulated. This collected data is pre-processed using the approaches for stop word removal, invalid character removal, and sentence segmentation after this data collection. These pre-processed data are then used to extract features using the DoG method. The final stage of prediction is performed by a novel AGCN where the parameters are tuned by DOA with consideration of error minimization as the fitness function. The overall proposed document prediction model is diagrammatically shown in Figure 1.

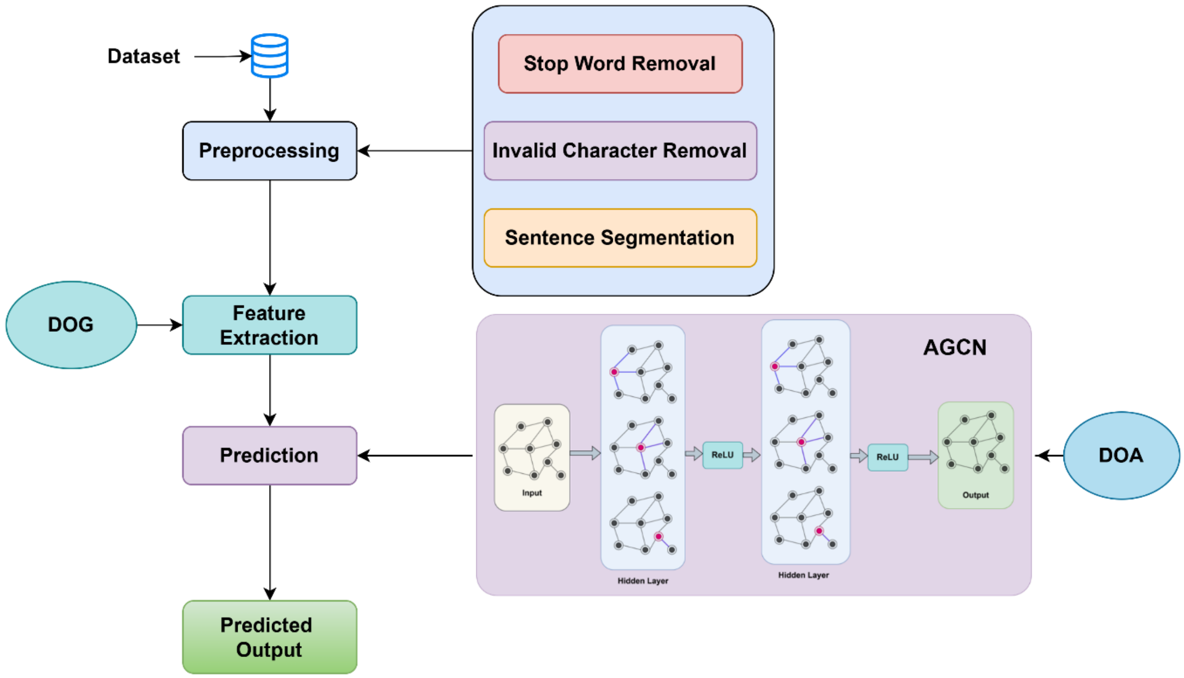


Figure 1. Overall Proposed Document Prediction Model

3.2 Data collection

The six manual sources used for the proposed published document prediction methodology are data mining, deep learning, image processing, machine learning, networks and sports. Each source has ten peer-reviewed publications. As seen in Figure 2, the sources can be represented diagrammatically as a word cloud.

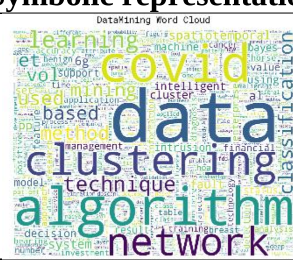
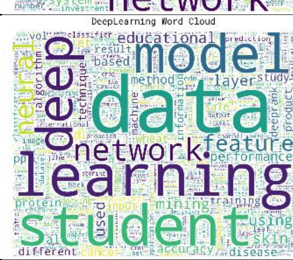
Dataset	**Symbolic representation**
Data mining	
Deep learning	

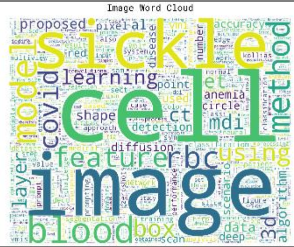
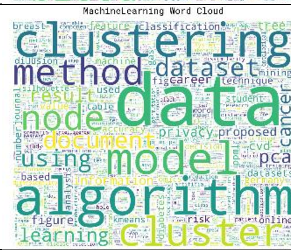
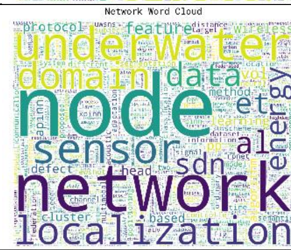
Image processing	
Machine learning	
Network	
Sports	

Figure 2. Diagrammatic Model describing the word cloud for the considered data sources

3.3 Pre-processing

Text pre-processing plays a critical role in various aspects of Natural Language Processing (NLP) as it converts the data into a more useful format for the better functioning of the algorithms.The pre-processing of the gathered data is done using the stop word removal, invalid character removal, and sentence segmentation approaches. Each of these concepts is clearly described below.

Stop word removal:The prepositions that come prior to the object do not contribute to the content of the document, so they need to be eliminated from the target documents.

Invalid character removal: The foremost activity involved in pre-processing is to eliminate all sorts of irrelevant characters such as punctuation marks, hyperlinks, and special symbols like, ?, !, /, @, $, #, ^, %, *, &, (,), which it is appropriate to assume are extraneous and as such, do not serve any purpose in the text analysis process and should be taken out completely.

Sentence segmentation:Every language is composed of a set of words that, when formed together, make up sentences, and several sentences create a document. Every sentence that is present in the document plays a major role in providing the needed information. In order to obtain such information, the proposed system splits the sentences at the dash "-". The placement of every key term in a sentence is determined from the starting point of each sentence because it is expected that key terms that contain important information pertaining to the subject of the sentences will always come first in each of the sentences.

3.4 Feature extraction by DoG

The features for the proposed document prediction model are extracted from the pre-processed data using the DoG approach. The DoG technique is used in this case for extracting features related to each patch Q_j of the image. The first spherical Gaussian support size in the DoG feature extraction filter is set to one. For a patch Q_j, the DoG feature at a point (y, z) is defined as.

$$E(y,z) = \left(H_1(y,z) - H_\sigma(y,z)\right) \times Q_j(y,z) \tag{1}$$

$$H_\sigma(y,z) = \frac{1}{2\pi\sigma^2} e^{-\frac{-(y^2+z^2)}{2\sigma^2}} \tag{2}$$

Here, the scale σ is considered as Gaussian filter parameter respectively.

3.5 Prediction by Novel AGCN

The extracted features of the proposed document prediction model undergo the final prediction stage using the novel AGCN. Here, the parameters of traditional GCN are optimized by DOA with the aim of attaining the fitness function as minimizing the error, thus called to be novel AGCN. A GCN is a variant of a NN that has multiple layers and can be applied to a graph directly in order to produce embedding vectors for nodes depending on the characteristics of their surrounding nodes. Let us define a simple graph $H = (W, F)$, where vertex set $W(|W| = o)$and edge set F exist. Browser assumes any two nodes to be connected to themselves; that is, $(w, w) \in F$for an arbitrary w. Let $Y \in S^{o \times o}$be a (n x n) matrix containing all o nodes feature matrices segmented in to n column, where n is the number of dimensions of the feature vectors, every y row $y_w \in S^n$ is a features vector pertaining w. Also consider an adjacency matrix B for graph H and its degree matrix E such that $E_{jj} = \sum_k B_{jk}$. The elements in the diagonal of B has a value of 1 due to the presence of self-loops. A GCN constructs an output representation with a single layer only about the nodes' direct neighbors. When several layers of a GCN is applied, the output tension is able to consider a wider area of nodes. In the case of a single layer GCN, the new node feature matrix, which is of l-dimensional space, $M^{(1)} \in S^{o \times l}$, is measured as:

$$M^{(1)} = \rho\left(\tilde{B} Y X_0\right) \tag{3}$$

The equation where $\tilde{B} = E^{\frac{-1}{2}} B E^{\frac{-1}{2}}$ represents the symmetrically normalized adjacency matrix and $X_0 \in S^{n \times l}$ stands for the weight matrix. ρ refers to an activation function such as a ReLU in which $\rho(y)$ is defined a $max(0, y)$. Further, it is possible to include the higher-order neighborhoods' information by adding more GCN layers on top of each other:

$$M^{(k+1)} = \rho\left(\tilde{B} M^{(k)} X_k\right) \tag{4}$$

Here, the layer number is described by k and $M^{(0)} = Y$ respectively. In terms of document evolution prediction, GCNs help represent and remember connections between documents in a structural way. GCNs utilize graph-based data providing context and semantics thus increasing precision. Another advantage is the ability of GCN to work with complex Non-Euclidean shapes making it easier to apply generalization effectively in document classification and recommendation inferences. However, GCNs can be heavy on computation power, memory and processing, more so when big graphs are present. Moreover, GCNs are sensitive to the quality of the graph in question. If the design is bad, the outcome will be worse. GCNs, moreover, tend to have limitations in scalability and risk of overfitting due to data sparsity, which reduces their usability. Therefore, the parameters of conventional GCN are tweaked by DOA algorithm with the aim of deriving the error minimization as the objective function, thus called to be novel AGCN. With the help of AGCNs, the quality of prediction of documents is enhanced by changing the structures of the graphs, which increases the degree of freedom of the model. They are quite efficient in modeling local and global dependencies, which improves the context comprehension. AGCNs also accomplish optimization tasks on a various range of datasets for enhancing the classification and recommendation capabilities while averting overfitting tendencies by means of adaptive learning strategies.

3.6 DOA

The DOA algorithm is selected here in the proposed document prediction model for tuning the parameters of existing GCN model with the consideration of attaining the error minimization as the fitness function. In DOA, the tactics and artistry of a dollmaker in crafting dolls are emulated. The initial creative idea of DOA stems from two innate actions in the process of doll making (i) altering the doll making materials in general and, (ii) altering the outer features of dolls in detail. The concept of DOA is first presented in an intuitive form and then in a mathematical model in two different stages starting with (i) the exploration stage which describes the process of making a large variety of different structures using doll-making materials and (ii) the implementing stages which involves making slight modifications to already created doll structures.

The DOA strategy operates as a population-based optimization method in which figurines constitute the population members. Population members assign values to design variables according to their position in the solution space. Thus, each doll can be treated as a candidate solution represented by a vector whose elements correspond to the decision variables. The various parts of the doll relate to the parameters of the problem under consideration. The population of the algorithm can be mathematically considered as based on a collection of these vectors together using a matrix according to Eq. (5). Also, the initial position of the incorporation members is initialized completely random using equation (6).

$$Y = \begin{bmatrix} Y_1 \\ \vdots \\ Y_j \\ \vdots \\ Y_O \end{bmatrix}_{O\times n} = \begin{bmatrix} y_{1,1} & \cdots & y_{1,e} & \cdots & y_{1,n} \\ \vdots & \ddots & \vdots & ⋰ & \vdots \\ y_{j,1} & \cdots & y_{j,e} & \cdots & y_{j,n} \\ \vdots & ⋰ & \vdots & \ddots & \vdots \\ y_{O,1} & \cdots & y_{O,e} & \cdots & y_{O,n} \end{bmatrix}_{O\times n} \quad (5)$$

$$y_{j,e} = LB_e + s \cdot (UB_e - LB_e) \quad (6)$$

Let's consider the population matrix of the DOAs (where Y is the population matrix of the DOAs, Y_j, is the j^{th} doll (i.e., candidate solution), $y_{j,e}$represents its e^{th} dimension in the search space (i.e., decision variable), O, represents the count of dolls (i.e., the population size), $n$represents thecount of decision variables, $s$represents a random count in the range [0,1], and lastly, LB_e and UB_erepresents the notations for the lower bound and upper bound of the e^{th} decision variable, correspondingly.

The aim of the problem being evaluated corresponds to the solution offered by every individual in a population. The different values of the objective function that have been computed can be put in a vector as provided by Eq. (7).

$$G = \begin{bmatrix} G_1 \\ \vdots \\ G_j \\ \vdots \\ G_O \end{bmatrix}_{O\times 1} = \begin{bmatrix} G(Y_1) \\ \vdots \\ G(Y_j) \\ \vdots \\ G(Y_O) \end{bmatrix}_{O\times 1} \quad (7)$$

As indicated by G denoting the objective function values vector, G_j embodies the objective function value acquired from the j^{th} chosen solution.

The calculated results of the objective function provide insights concerning the performance of the candidate solutions (i.e., population members). In this manner, the optimal calculated value for the objective function is associated to the fittest candidate in terms of population. The distances or positions of the population members and hence the values of the objective function changes from one iteration to the next as DOA is an iteration based strategy. Hence it follows that with each of the iterations, there is need to update and hold the position of the best member of the population. In general application of the DOA, this position corresponding to the best member is seen as the answer of the problem under consideration.

The simulation of the process of creating a doll provided the basis for deriving the DOA mathematical model. The updating of the positions of the DOA population members is done using how the dollmaker's strategies change/differ when the doll is being made. Simply, the making of a doll can be broken down into two key processes, (i) raw doll making activities i.e. stuffing and sewing without pattern requirements and (ii) imbuing the finished doll with life by focusing on aesthetics like the face, hair and clothing of the doll. Every iteration updates the positions of the members of the DOA in two key steps (i) exploration step explains how the pattern is selected and the doll making materials sewn together and (ii) exploitation step that demonstrates the beautifying of the doll. Each of these phases is described and formulated in mathematical terms.

Selecting a design and stitching a set of dolls results in considerable transformations to the final doll. It is possible to stick those transformations to the doll changes in the populations which leads to considerable change in the position of populations thus enhancing the search ability of the algorithm more globally. In DOA designs, the best individual is treated as the best alternative of the pattern for the doll $(Q = Y_{Best})$. Similarly, the vector values of every unit illustrate the materials for the dolls that should be stitched according to the design adopted.

The mathematical modeling of the process of doll-making and sewing with the right application of the above selected pattern, inspires the determination of a new position for every DOA member given by equation (8). Should this new position improve any corresponding DOA member objective function as per equation (9) the previous position of that particular DOA member will be substituted for the new position.

$$y_{j,k}^{Q1} = y_{j,k} + s \cdot \left(Q_k - J \cdot y_{j,k}\right) \quad (8)$$

$$Y_j = \begin{cases} Y_j^{Q1}, & G_j^{Q1} \leq G_j \\ Y_j, & otherwise \end{cases} \quad (9)$$

In this context, Q refers to the pattern of the doll which is chosen, Q_k refers to the k^{th} coordinate of the selected doll's pattern, Y_j^{Q1} connotes the shifted position of the j^{th} member after the first phase of DOA $y_{j,k}^{Q1}$ describes the k^{th} dimension of this j^{th} member, G_j^{Q1} stands for the associated objective function value of the j^{th} member while the letter s dots a number between 0 and 1, and the letter J refers to a uniformly generated random number with discrete values of 1 and 2.

The process wallowing in the aesthetic coping of the doll, here regarding dimensions, facial features and expressions, clothing, and hair, amongst other components results in infinitesimal yet definite alterations in the doll's overall design. Such modeling of small scale doll alterations, results in slight alterations of the coordinates of the members of the population and consequently enhances the performance of the local search capabilities of the algorithm. In DOA design a dollmaker is assumed to gradually bring the appearance of the doll closer to a predetermined appearance.

Drawing from the simulation of this process, it has been determined a new position for all the DOA members using Eq. (10). Next, if the objective function's value improves, then according to Equation (11), the current position of the relative member gets substituted for the earlier position.

$$y_{j,k}^{Q2} = y_{j,k} + \left(1 - 2\, s_{j,k}\right) \cdot \frac{UB_k - LB_k}{u} \tag{10}$$

$$Y_j = \begin{cases} Y_j^{Q2}, & G_j^{Q2} \leq G_j \\ Y_j, & otherwise \end{cases} \tag{11}$$

Here, Y_j^{Q2} is the newly obtained position for the j^{th} member in DOA's second phase, $y_{j,k}^{Q2}$ being its k^{th} dimension, G_j^{Q2} denoting its fitness function value, s being a random count sampled between [0,1] and u being the current iteration number.

The first iteration of DOA involves moving every member of the population according to the first and second phases and comes to a conclusion. T8he data updating for the population members position continues as per Eqs. (8) through (11) and so on till the last iteration of the algorithm. With every following second, the most appropriate position of such treated candidate is recorded and treated as the best solution to the problem under algorithmic consideration. Following the exhaustive application of DOA, the algorithm indicates the best candidate solution rendered to the addressed concerns as the outcome. The implementation flow of the DOA steps is shown in Algorithm I.

Algorithm 1: *DOA*

Begin DOA

Input problem data such as fitness function, variables, and conditions [extracted features of the developed document prediction model]

Set iterations (U) *and DOA population size* (O)

$$y_{j,e} = LB_e + s \cdot (UB_e - LB_e)$$

Evaluate the fitness function [error minimization of the proposed document prediction model]

For $u = 1$ *to* U

For $j = 1$ *to* O

Perform exploration phase

Describe the doll making pattern as $Q \leftarrow Y_{Best}$

$$y_{j,k}^{Q1} = y_{j,k} + s \cdot \left(Q_k - J \cdot y_{j,k}\right)$$

$$Y_j = \begin{cases} Y_j^{Q1}, & G_j^{Q1} \leq G_j \\ Y_j, & otherwise \end{cases}$$

Perform exploitation phase

$$y_{j,k}^{Q2} = y_{j,k} + \left(1 - 2\, s_{j,k}\right) \cdot \frac{UB_k - LB_k}{u}$$

$$Y_j = \begin{cases} Y_j^{Q2}, & G_j^{Q2} \le G_j \\ Y_j, & otherwise \end{cases}$$

end
Save the optimal candidate solution attained so far
end
Output the best quasi-optimal solution attained with the DOA
Stop DOA

4. Results and analysis

4.1 Experimental setup

The proposed AGCN-DOA for the document prediction model was implemented in MATLAB and the findings were analyzed. The maximum iteration count was considered to be 100. The proposed AGCN-DOA was compared with distinct traditional models like MultiSChuBERT [7], CAG [13], ACNNDS [14], and DADRM [15] with consideration of analysis like prediction accuracy, MSE, MAE, MAPE, and RMSE to demonstrate the superiority of the proposed document prediction model.

4.2 Prediction accuracy analysis

As seen in Table 1 and Figure 3, the predictive accuracies of several models under different numbers of iterations are illustrated. The proposed AGCN-DOA outperformed all other methods with respect to the highest prediction accuracy. AGCN-DOA model has shown remarkable forecasting ability as the number of iterations increased, particularly towards the latter iterations. The proposed AGCN-DOA for the document prediction model in terms of prediction accuracy is 11.18%, 11.01%, 13.24%, and 14.16%better than MultiSChuBERT, CAG, ACNNDS, and DADRM respectively.

Table 1 Prediction accuracy analysis

Methods	Iterations				
	20	40	60	80	100
MultiSChuBERT [7]	47.29	59.64	76.37	60.49	89.48
CAG [13]	49.16	59.31	60.26	79.74	89.62
ACNNDS [14]	48.54	56.25	68.76	77.27	87.85
DADRM [15]	58.93	49.55	78.46	69.59	87.14
Proposed AGCN-DOA	59.14	67.23	78.61	89.01	99.48

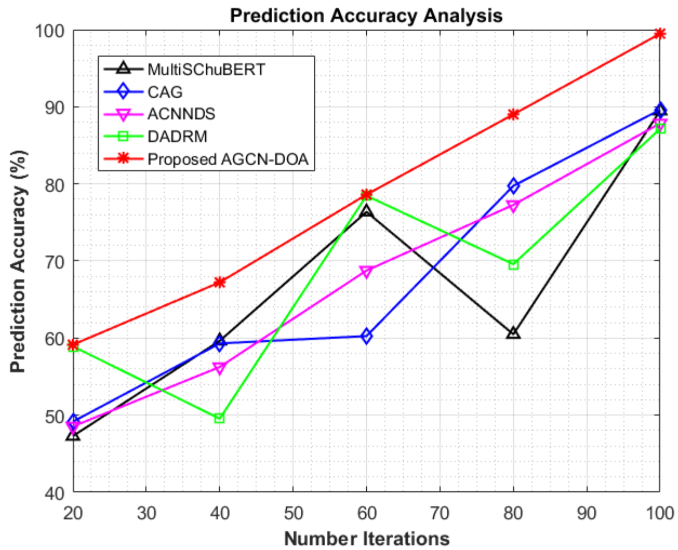


Figure 3. Prediction accuracy analysis

4.3 MSE analysis

Figure 4 and Table 2 draws the comparison of MSE across several document prediction models for different iterations. The Proposed AGCN-DOA has a significant spike but then drops very fast showing improvement at high iteration levels. The falling MSE of AGCN-DOA after several iterations shows that the models performance improves with more iterations. The proposed AGCN-DOA for the document prediction model with respect to MSE is 94.73%, 94.92%, 93.69%, and 92.65%lower than MultiSChuBERT, CAG, ACNNDS, and DADRM respectively.

Table 2MSE analysis

Methods	Iterations				
	20	40	60	80	100
MultiSChuBERT [7]	0.2905	0.5317	0.3725	0.4314	0.1839
CAG [13]	0.2713	0.4574	0.3694	0.5823	0.1911
ACNNDS [14]	0.4735	0.5881	0.2829	0.3703	0.1537
DADRM [15]	0.2371	0.5663	0.4769	0.3762	0.1320
Proposed AGCN-DOA	0.4221	0.3995	0.2673	0.1034	0.0097

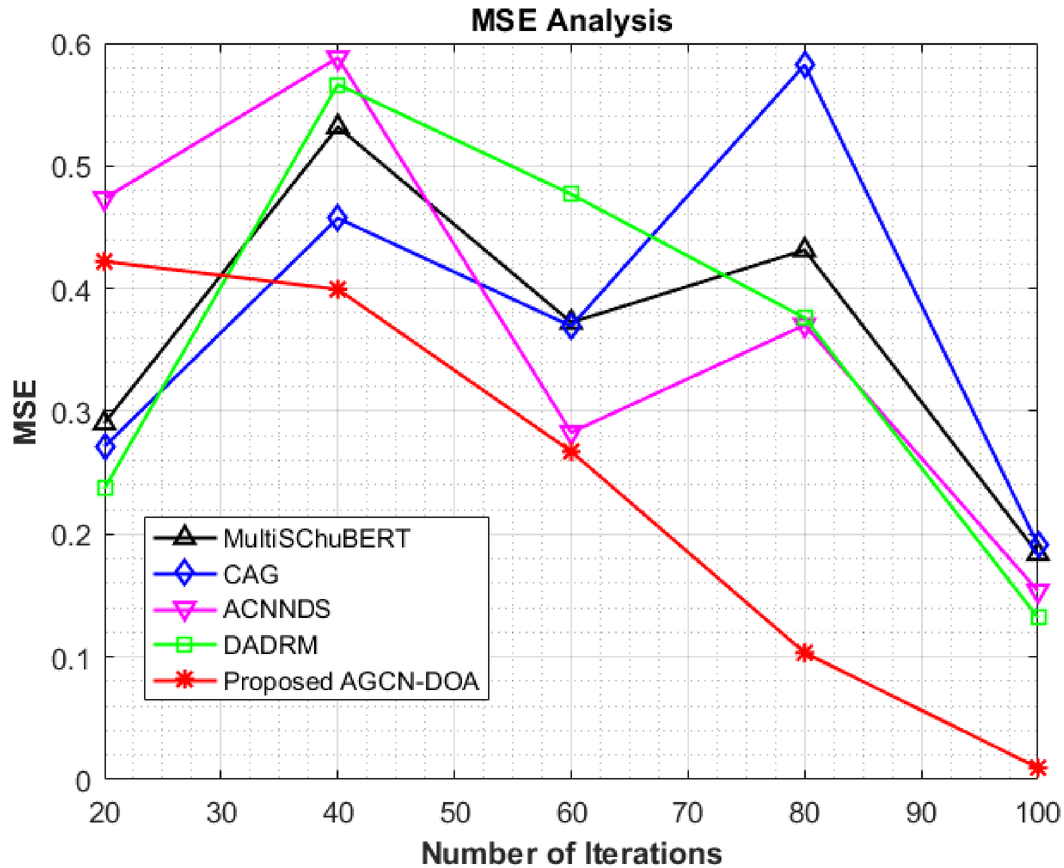


Figure 4. MSE analysis

4.4 MAE analysis

Table 3 and Figure 5 shows the MAE for different document prediction models in different iterations. The Proposed AGCN-DOA yields lesser values of MAE throughout the process demonstrating that accuracy improves with iteration. The existing techniques reveal variation in performance with certain iterations exhibiting high values. The falling trend of MAE for AGCN-DOA shows that the model was able to minimize the prediction error with increase in the iterations of the model.The proposed AGCN-DOA for the document prediction model in terms of MAE is 31.71%, 47.44%, 33.55%, and 41.65%lower than MultiSChuBERT, CAG, ACNNDS, and DADRM respectively.

Table 3MAE analysis

Methods	Iterations				
	20	40	60	80	100
MultiSChuBERT [7]	0.6341	0.3801	0.4272	0.5343	0.2138
CAG [13]	0.5608	0.4238	0.6594	0.3192	0.2778
ACNNDS [14]	0.4901	0.3861	0.5597	0.6288	0.2197
DADRM [15]	0.5304	0.4319	0.6731	0.3971	0.2502
Proposed AGCN-DOA	0.5215	0.4287	0.3830	0.2776	0.1460

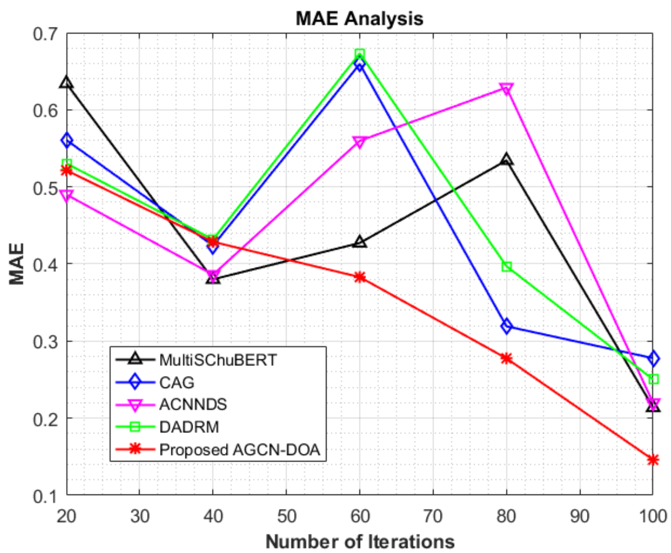


Figure 5. MAE analysis

4.5 MAPE analysis

As shown in Table 4 and Figure 6, the MAPE of different document prediction models was calculated through several iterations. The Proposed AGCN-DOA for each case gives the lowest MAPE values suggesting more accurate predictions. Best predictive trustworthiness AGCN-DOA has as the number of iterations increases. The proposed AGCN-DOA for the document prediction model with respect to MAPE is 47.73%, 58.93%, 57.14%, and 61.02% lower than MultiSChuBERT, CAG, ACNNDS, and DADRM respectively.

Table 4MAPE analysis

Methods	Iterations				
	20	40	60	80	100
MultiSChuBERT [7]	0.0231	0.0558	0.0312	0.0401	0.0132
CAG [13]	0.0476	0.0354	0.0557	0.0246	0.0168
ACNNDS [14]	0.0459	0.0268	0.0316	0.0576	0.0161
DADRM [15]	0.0475	0.0572	0.0274	0.0315	0.0177
Proposed AGCN-DOA	0.0429	0.0364	0.0283	0.0147	0.0069

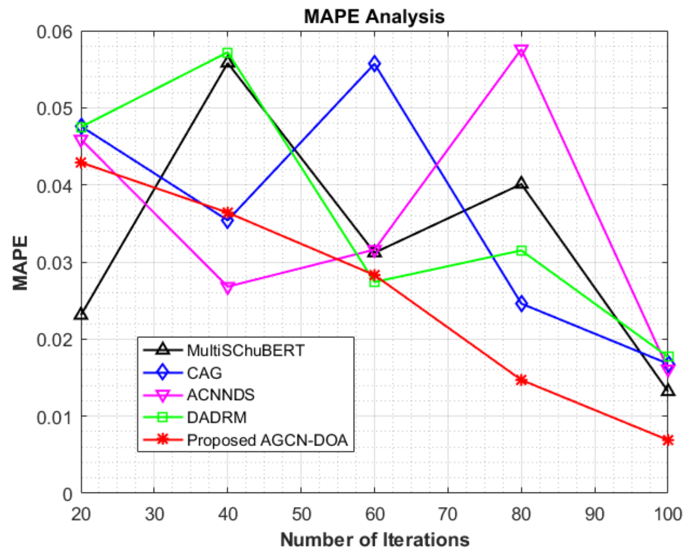


Figure 6. MAPE analysis

4.6 RMSE analysis

In Table 5 and Figure 7 below, the RMSE values are reported for various document prediction models across different cycles of iterations. The Proposed AGCN-DOA model outperformed the other models the most registering a low RMSE value, which is an indication of high accuracy. The findings also reaffirm the reduction in the prediction error rates by AGCN-DOA. The proposed AGCN-DOA for the document prediction model in terms of RMSE is 77.03%, 77.47%, 74.87%, and 72.89% lower than MultiSChuBERT, CAG, ACNNDS, and DADRM respectively.

Table 5RMSE analysis

Methods	Iterations				
	20	40	60	80	100
MultiSChuBERT [7]	0.5390	0.7292	0.6103	0.6568	0.4288
CAG [13]	0.5209	0.6763	0.6078	0.7631	0.4371
ACNNDS [14]	0.6881	0.7669	0.5319	0.6085	0.3920
DADRM [15]	0.4869	0.7525	0.6906	0.6134	0.3633
Proposed AGCN-DOA	0.6497	0.6321	0.5170	0.3216	0.0985

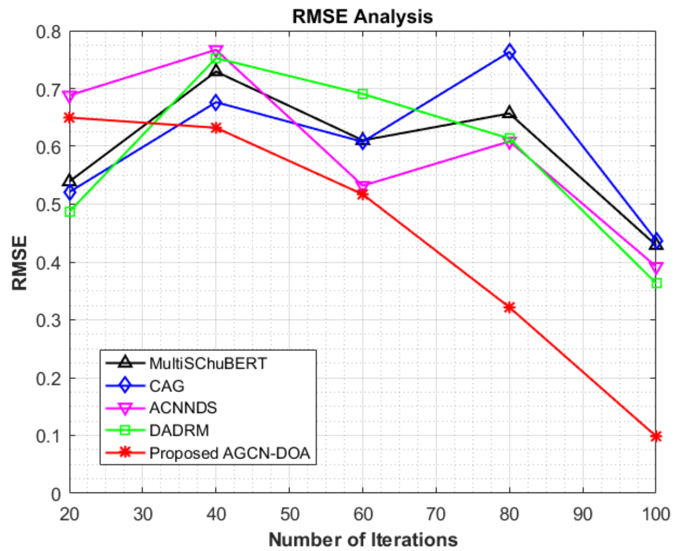


Figure 7. RMSE analysis

4.7 Discussion

The outcomes suggest that the AGCN-DOA model has been the best performing model of all the document prediction models in all measures (i.e., prediction accuracy, MSE, MAE, MAPE, RMSE). AGCN-DOA also improved the prediction accuracy significantly, where it was noted that accuracy increased by as much as 14.16% in favor of competing processes as the number of iterations was raised. A similar pattern was observed in MSE where AGCN-DOA achieved a remarkable cut back of 93.83% compared to the worst performing iteration of MultiSChuBERT. The MAPE and MAE analysis results also re-iterated the superiority of AGCN-DOA above the alternatives showing an over 61% lower MAE and MAPE than the best performing alternatives. The RMSE results also showed that AGCN-DOA was able to reduce the prediction error with the most reductions shown of 77%. These results indicate that AGCN-DOA not only improves the predictive performance but reduces the increase of error rates with higher iterations, making it a competent model for use in document prediction tasks.

5. Conclusion

In this work, an advanced methodology oriented towards deep learning was utilized to predict documents. Initially, a set of data containing a collection of documents and their respective classes was sourced from the web. In the next step, the collected information undergoes preprocessing that included stop word removal, invalid character removal, and sentence segmentation approaches. After that, the features were obtained from the already cleaned samples of data using the DoG technique. The last prediction stage was performed by the newly developed AGCN whose parameters were optimally tuned using the DOA that minimized the given error function for tuning the parameters. The results suggested that, this model outperformed various other models relative to this taken approach of modeling.The proposed AGCN-DOA for the document prediction model in terms of prediction accuracy, MSE, MAE, MAPE, and RMSE was 11.18%, 94.73%, 31.71%, 47.73%, and 77.03% better than the considered existing methods respectively.

Data Availability: The datasets generated and/or analyzed during the current study are collected from online sources that consist of a group of documents together with their corresponding categories such as data mining, deep learning, image processing, machine learning, networks and sports.

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