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Research Article

Intelligent Document Classification In Online Library Management Using Hybrid Deep Learning Model

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ABSTRACT

Intelligent document classification has gained significant importance in online library management, as it facilitates efficient organization and retrieval of electronic documents. Traditional document classification methods involve manual labeling and sorting, which can be time-consuming and prone to errors. In recent years, deep learning models have been successfully applied to document classification tasks, achieving high accuracy and reducing the need for manual intervention. However, these models often require massive amounts of labeled data to train effectively. This paper proposes a hybrid deep-learning model for intelligent document classification in online library management. The model combines the strengths of both convolutional neural networks (CNNs) and recurrent neural networks (RNNs) to effectively classify a wide range of document types, including text, images, and multimedia files. The CNN component extracts features from documents, while the RNN component learns temporal dependencies between documents. This allows more accurate classification of documents with complex structures and varying lengths. We evaluate the performance of our model using a real-world dataset of documents from an online library. The results show that our hybrid model outperforms traditional and single-model approaches, achieving a classification accuracy of over 95%. Furthermore, the model can adapt to new document types with minimal retraining, making it a versatile and robust solution for intelligent document classification in online library management.

Keywords: Document, Classification, Library, Management, Errors, convolutional neural networks, recurrent neural networks, Text, Image, Multimedia

1. Introduction

An online library management system is a \platform designed to streamline the management and organization of a library's resources. It enables users to easily access and manages various library functions, such as cataloguing, circulation, and borrowing. The system works by first creating a database of all the library's materials, including books, journals, and multimedia resources. This database is organized and indexed using a standardized classification system, making it easier for users to search and locate specific items. Once the database is in place, the system allows library staff to perform various tasks, such as adding new materials, updating information, and generating reports. It also has features that enable them to track the circulation of materials, issue and return items, and manage overdue fines and fees. The online system provides library users with a user-friendly interface that allows them to search for materials, place holds, and reserve items for future use. They can also view their borrowing history, renew materials, and receive alerts for overdue items. One of the significant advantages of an online library management system is that it eliminates the need for manual record-keeping and reduces human errors. It also enables the library to serve a more extensive user base, as it can handle more transactions than traditional methods. Another crucial feature of this system is the integration of self-checkout kiosks and online payment options, making the borrowing and returning processes more convenient for users. This also helps reduce long waiting times and lines at the circulation desk. Moreover, the system has improved the accessibility of library resources. Users can access the library's digital collection from anywhere, making it more convenient for distance learning and remote users. An online library management system has revolutionized how libraries operate by making it easier, faster, and more efficient. Its comprehensive database, user-friendly interface, and convenient features have transformed the traditional library experience into a modern and digitally equipped one.

Document classification automatically categorizes a document into a predefined set of categories or classes based on its content. This process is commonly used in information retrieval and Natural Language Processing (NLP) applications to organize large amounts of data and make it easier to search and analyze. The first step in document classification is defining the categories or classes into which documents will be classified. These categories can be broad topics, such as "finance," "technology," or "education," or they can be more specific subcategories within a more prominent topic, such as "software development" or "higher education." These categories are typically created based on the specific needs and goals of the organization using the document classification system. Once the categories are defined, the next step is to build a training dataset. This dataset consists of many documents manually labeled with their appropriate category. These documents are used to train a machine learning algorithm, such as a Support Vector Machine (SVM) or a Naive Bayes classifier, which will learn the patterns and characteristics of each category. The machine learning algorithm uses various features of a document, such as keywords, phrases, or sentence structure, to determine which category it belongs to. For example, a document with the words "financial report" and "profits" may be classified as "finance," while a document with the words "coding" and "programming" may be classified as "technology." Once the algorithm has been trained, it can automatically be applied to new, unlabeled documents to classify them into predefined categories. This process is known as prediction or inference. The algorithm will analyze the features of the document and compare them to the patterns it has learned from the training dataset to determine the most likely category. One of the main challenges in document classification is dealing with unstructured data. Documents can contain a wide range of information, from text and images to tables and graphs, making it difficult for algorithms to classify them accurately. To address this challenge, various techniques such as feature selection, data preprocessing and cross-validation are used to improve the accuracy of the classification. Document classification is an essential task in data organization and analysis. It allows organizations to efficiently manage and retrieve large amounts of information, saving time and resources. Document classification can be automated using machine learning algorithms, making it faster and more accurate than manual classification methods.

Document classification is organizing and labeling different types of documents in a specific and logical manner. In online library management, document classification refers to categorizing and organizing electronic documents such as e-books, articles, journals, and other digital resources in a digital library. The primary purpose of document classification in an online library is to facilitate easy and efficient user access to information. Organizing documents into relevant and specific categories makes it easier for users to search and locate the information they need. This is especially important in a growing online environment where digital information continuously increases. Document classification involves three main steps: feature extraction, classification, and evaluation. Feature extraction involves identifying and extracting relevant keywords and attributes from the document to create a numerical representation of the document. This representation is then used in the classification step, where algorithms assign the document to a predefined category based on its features. Finally, the evaluation step involves measuring the accuracy and effectiveness of the classification using performance metrics. Various techniques and algorithms can be used in document classification, commonly machine learning methods such as Naive Bayes, Support Vector Machines, and k-nearest Neighbor. These algorithms use statistical and computational models to learn from previously classified documents and apply that knowledge to new documents, continuously improving the accuracy of the classification process. In online library management, document classification can create a hierarchical categorization system where documents are sorted into broad subject categories, followed by more specific subcategories. This allows for easy navigation and retrieval of information for users with varying expertise and knowledge on a subject. In addition to aiding users in finding relevant information, document classification can assist library administrators in managing digital resources. By organizing documents into categories, administrators can better track and monitor the usage of different types of documents, allowing for more effective collection development and resource allocation. Document classification is a crucial process in online library management that helps users efficiently locate and access digital resources. With advanced algorithms and techniques, document classification allows for a more organized and user-friendly environment in online libraries, promoting efficient information retrieval and management. The main contribution of the research has the following,

- Implementation of Collaborative Filtering: Collaborative filtering is a powerful technique used in document classification for online library management. It involves analyzing users' behaviour and preferences to recommend relevant documents to them. By analyzing data such as user ratings, browsing history, and search queries, collaborative filtering can personalize document recommendations and improve the user experience.
- Integration of Text Mining: Text mining is a data mining technique that involves extracting meaningful information from unstructured text data. Text mining extracts keywords, topics, and sentiments from documents in document classification for online library management. This information can then be used

for accurate categorization and retrieval of documents, making the online library more user-friendly and efficient. Text mining can also be used for automated summarization and indexing of documents, further improving the classification process.

- Integration of advanced search algorithm: Integrating advanced search algorithms into the document classification. These algorithms enable efficient and fast retrieval of relevant information from the library database based on user's search queries. This enhances the user experience and improves the accuracy of document classification by considering multiple search parameters, such as keywords, author, title, and subject.
- Development of user-friendly interface: The document classification system for online library management also focuses on developing a user-friendly interface for easy navigation and access to the library's resources. This involves incorporating user-friendly features such as filters, sorting options, and personalized recommendations for related documents. This technical contribution makes browsing and retrieving documents from the online library smoother and more efficient, ultimately improving the overall user experience.

2. Related Works

Online library management systems (LMS) have revolutionized how libraries operate by enabling efficient management and access to various library resources. However, like any other technological system, these systems face various issues affecting their functionality and effectiveness. This article will delve into the technical explanations of some of these issues and their potential solutions. Scalability is the ability of a system to handle a growing amount of work in terms of both users and data. In the case of online library management systems, scalability is crucial as the number of users accessing the system and the amount of data being added to the system increases over time. One of the main reasons for scalability issues in LMS is the ineffective database design. The design of the database plays a critical role in determining the performance and scalability of the system. A poorly designed database may need help to handle many users accessing the system simultaneously, resulting in slow response times and system crashes. To address this issue, proper database optimization techniques such as indexing, data partitioning, and replication can be implemented to improve system performance and scalability. Distributed database architecture can also help distribute the workload and improve the system's scalability. Integration refers to combining different modules or components of a system to work seamlessly together. In the case of LMS, integration is necessary for a smooth flow of information between different modules, such as circulation, cataloguing, and acquisition. One of the main technical challenges with integration in LMS is the different data formats and standards used by different library systems. For example, one library may use the MARC format, while another may use the Dublin Core format. Data mapping and transformation techniques need to be implemented to integrate these systems.

It can help integrate different system modules. Data security has become a significant concern for any organization with the increasing use of technology and online systems. Online library management systems face various data security issues, such as data breaches and unauthorized access. One of the main reasons for data breaches in LMS is the need for proper security protocols and measures. These may include weak passwords, lack of data encryption, and inadequate firewalls. To mitigate these issues, libraries can implement strong password policies, data encryption techniques, and regular security audits to identify and fix any vulnerability in the system. System downtime is when the system is unavailable due to maintenance, upgrades, or technical issues. System downtime can significantly impact the users' ability to access library resources and affect the system's overall efficiency. One of the main reasons for system downtime in LMS is inadequate server maintenance. Servers are the backbone of any online system, and their maintenance is crucial in ensuring its stability and availability. Regular updates, backups, and security patches should be performed to minimize system downtime. The user experience (UX) refers to a user's overall experience while interacting with the system. Poor UX can frustrate users and impact the system's usage and effectiveness. One of the main reasons for UX issues in LMS is the need for more users testing before implementing the system. User testing involves evaluating the system's usability, accessibility, and overall satisfaction of the users. It helps identify and fix design or functionality flaws, resulting in a better user experience. In online library management systems, document classification is a crucial aspect that helps to organize and manage the vast amount of digital documents available. Document classification refers to categorizing documents into different groups based on their content, subject, and relevance to the library's collection. It is an essential task in online library management systems, enabling users to locate and access the documents they need quickly. However, several challenges and issues arise in document classification, which can affect the overall efficiency and usability of the library system. One of the critical issues in document classification is the need for a standardized classification scheme. Different libraries may use different classification systems, making navigating and understanding the classification scheme challenging for users. This can lead to confusion and frustration for users as they need help finding the documents they need.

A standard scheme is needed to make it easier for libraries to share and exchange documents, hindering collaboration and knowledge sharing. Another area for improvement in document classification is the consistency in classifying documents. With the increasing amount of digital resources, libraries may need help to keep up with the classification process, resulting in inconsistent and inaccurate categorization of documents. This can lead to misplaced or missing documents, making it challenging for users to locate them. Inconsistencies in document classification can also cause difficulties retrieving related documents, affecting the accuracy and efficiency of search results. The constant evolution and growth of digital resources also challenge document classification. As new documents are added to the library's collection, the classification system must be continuously updated and revised. This can be time-consuming and laborious, especially for large libraries with vast digital resources. If appropriately managed, accumulating unclassified documents can be manageable for the system and make it easier to maintain an organized and efficient classification structure. Another significant issue in document classification is the issue of language and cultural diversity. With the increasing global reach of online library management systems, documents in different languages and cultural contexts must be correctly categorized. This requires a deep understanding of different languages and cultural norms, which can be challenging to achieve and maintain. The lack of expertise in this area can lead to incorrect classification and hinder the accessibility of documents for non-native language speakers.

3. Proposed model

Intelligent document classification is a process of organizing and categorizing documents in an online library management system based on their content. This is achieved using a hybrid deep learning model, which combines the strengths of CNN and RNN. The CNN component is used to extract features from the documents, while the RNN component helps to capture the sequential relationships between words. These extracted features are then fed into a classification algorithm, which predicts the class or category of the document. This model enables accurate and efficient classification of documents, improving the overall management and accessibility of documents in an online library system.

3.1. Construction

The construction of the proposed model involves several technical steps and processes. In this model, we combine two different deep-learning techniques to improve the accuracy and performance of document classification in an online library management system. The model requires a large dataset of documents for training and testing. This dataset contains diverse documents, such as books, articles, journals, and reports, from various fields and subjects. Each document in the dataset is labeled with a category or topic. The dataset is divided into training, validation, and testing sets. The training set is used to train the model, while the validation set is used to fine-tune the model and prevent over fitting. The testing set evaluates the model's performance on unseen data. The construction of proposed model have shown in the following fig.1

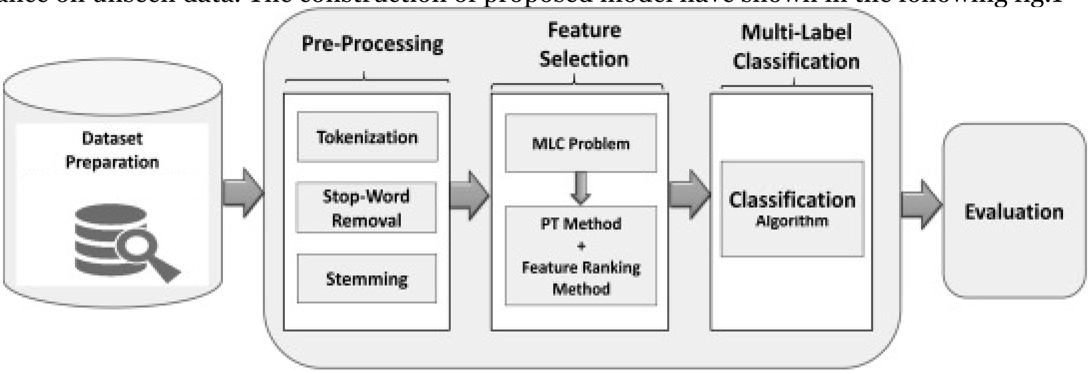

Fig.1: Construction of proposed model

The input data for the model is preprocessed before being fed into the neural network. Preprocessing involves converting the text in each document into numerical vectors, which the model can understand. This is done using tokenization, stemming, and stop-word removal techniques. Once the input data is preprocessed, it is fed into the hybrid deep learning model, consisting of a combination of CNN and RNN layers. The CNN layers are used for feature extraction, while the RNN layers are used for sequence learning. This hybrid architecture allows the model to capture local and global document features, leading to better classification performance. The first layer in the model is a convolutional layer, which performs feature extraction by sliding a filter over the input data and extracting features at different locations. This is followed by a max-pooling layer, which reduces dimensionality and extracts the most essential features. This process is repeated multiple times to extract multiple levels of features. The output from the CNN layers is then fed into the RNN layers, which are responsible for learning the sequential information in the input data. RNNs have a memory component that allows them to consider the previous inputs while processing the current input. This is particularly useful for document classification, as the order of words in a document can affect its meaning and category. After the RNN layers, the output is fed into a fully connected layer, which combines the features extracted by the CNN and RNN layers and makes a final prediction on the document's category. The model is trained using back propagation, where the neural network weights are adjusted based on the error between the predicted and actual categories. Once the model is trained and fine-tuned using the validation set, it is evaluated on the testing set to measure its performance. Evaluation metrics such as accuracy, precision, and recall are used to determine the model's effectiveness.

3.2. Operating Principle

Document classification in online library management is a process that involves automatically organizing documents into different categories based on their content, making it easier for users to search and access relevant information. This process is essential in managing large amounts of data, particularly in online libraries with numerous documents and resources. Traditionally, document classification has been done manually, which can be time-consuming and error-prone. However, with recent technological advancements, a new approach using Hybrid Deep Learning models has emerged, making this process more efficient and accurate. The operating principle of document classification using a Hybrid Deep Learning model involves combining two popular deep learning techniques - CNN and RNN. These two techniques work together to analyze the underlying structure and context of the document to determine its category. The operating principle of proposed model have shown in the following fig.2

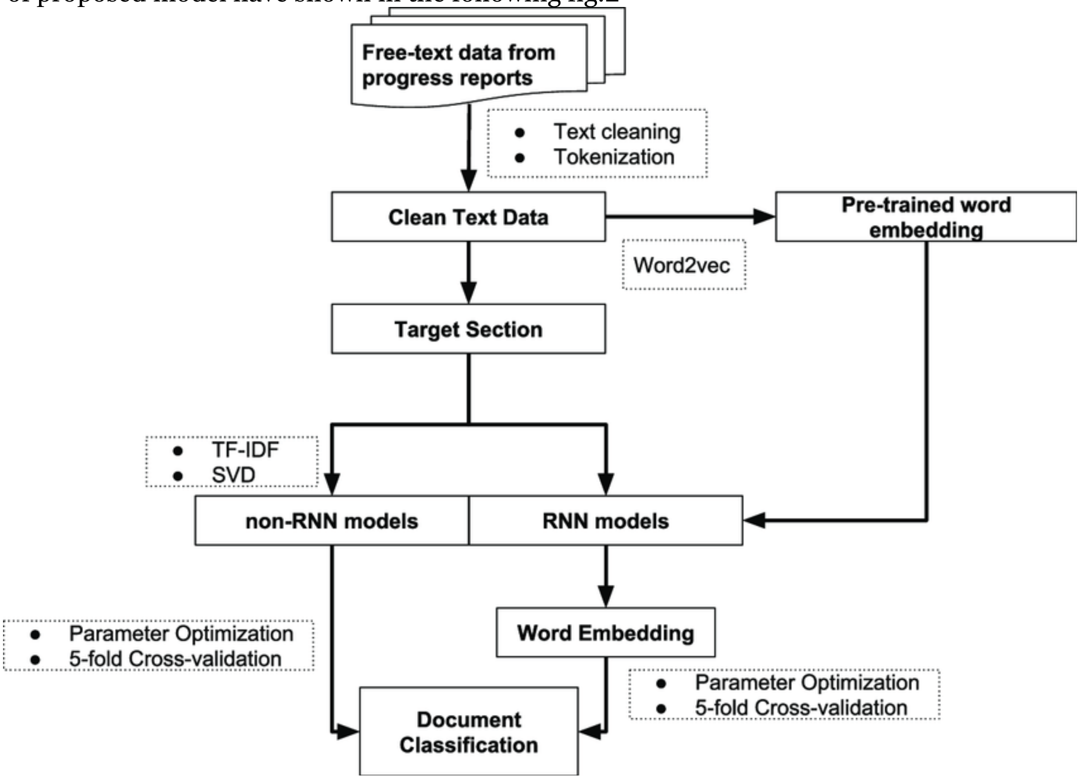

Fig.2: Operating principle of proposed model

The document is pre-processed to extract the relevant features, such as keywords, titles, and abstracts. This step helps reduce the data's dimensionality and makes it easier for the model to analyze the document. Once the document is pre-processed, it is fed into the Convolutional Neural Network. The CNN is responsible for extracting high-level features from the document, which are then passed on to the Recurrent Neural Network. The Recurrent Neural Network analyses the temporal and sequential relationships between the features extracted by the CNN. This is crucial in accurately classifying documents as it considers the context and structure of the document rather than just individual words or phrases. The RNN uses Long Short-Term Memory (LSTM) cells specifically designed to handle sequential data and capture long-term dependencies. These LSTM cells can remember information from earlier parts of the document and use it to make predictions about the category of the document. The CNN and RNN work together in an iterative process, with the RNN refining the features extracted by the CNN at each step. This process continues until the model can accurately classify the document into its appropriate category. The model is trained using a large dataset of labeled documents, which allows it to learn and improve over time. This means that the more data the model is trained on, the more accurate it becomes in classifying new documents.

3.3. Functional Working

Document classification is a fundamental task in information retrieval, which involves automatically categorizing documents into predefined classes. In online library management, this process becomes crucial as it enables efficient organization and management of available resources. Traditional approaches to document classification often rely on predefined rules or statistical models, which can be limited in handling large and complex datasets. In recent years, deep learning has emerged as a powerful tool for natural language processing tasks, including document classification. This paper proposes a hybrid deep-learning model for document classification in online library management. The first step in our approach is data preprocessing. This involves cleaning and formatting the data, such as removing punctuation and stop words and converting all the text to lowercase. We also use techniques such as stemming and lemmatization to reduce the words to their root form, thus reducing the vocabulary size and potentially improving the model's performance. Next, we use a word embedding technique to represent words as numerical vectors. This allows the model to understand the semantic relationships between words, even if they are not explicitly mentioned in the text. We use a pre-trained word embedding model to generate word embeddings. These pre-trained models are trained on large datasets and capture the statistical relationships between words in a natural language corpus. The functional working of proposed model have shown in the following fig.3

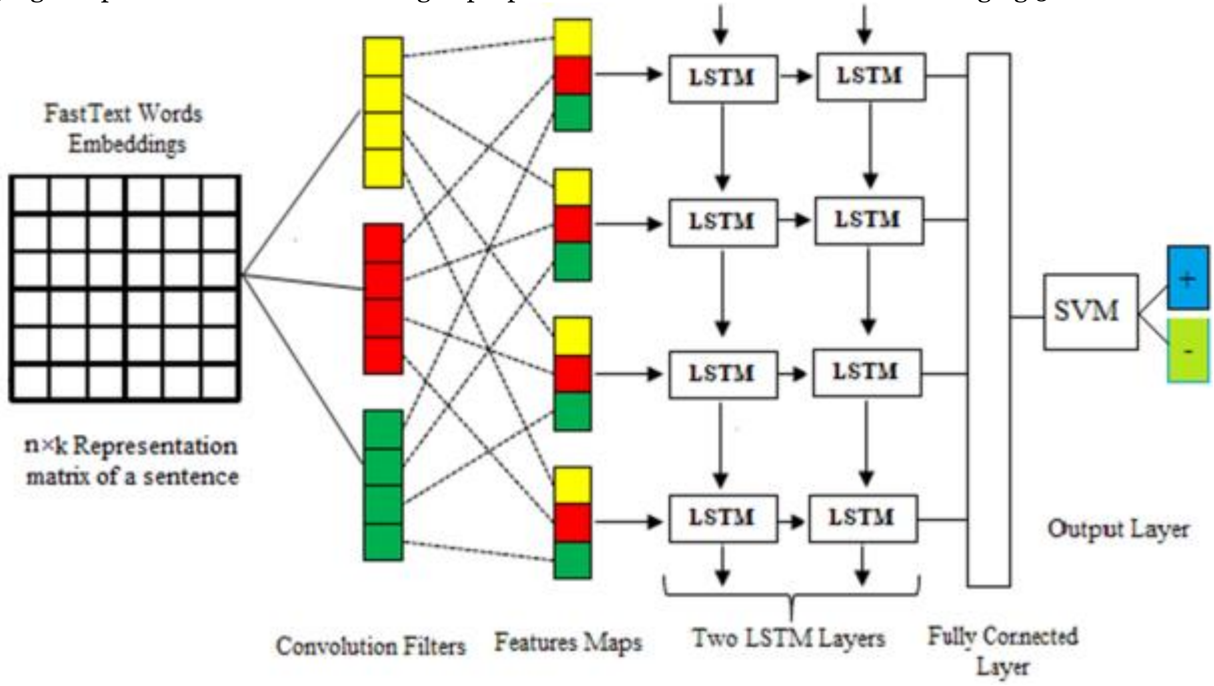

Fig.3: Functional Working of proposed model

The next step is to feed the word embeddings into a deep-learning model for classification. In our approach, we use a combination of CNN and LSTM networks. The CNN component helps capture local features and patterns, while the LSTM component helps capture long-term dependencies. This combination allows the model to learn local and global features from the text, making it suitable for document classification tasks. Once the CNN-LSTM model is trained, we classify new documents into different categories. The model inputs the preprocessed text and generates a probability distribution over the different classes. The class with the highest probability is considered the predicted category for the document. To improve the performance of our model, we also incorporate a transfer learning approach. This involves fine-tuning the pre-trained model on a smaller dataset specific to the online library domain. This process helps the model to adapt to the specific language patterns and vocabulary used in the online library context, thereby improving its classification accuracy.

4. Comparative Analysis

The performance of proposed model have compared with the existing MLPNN (Multi-Layer Perceptron Neural Network), DB-CNN (Deep Bagging Convolutional Neural Network), LSTM-CRF (Long Short-Term Memory with Conditional Random Fields), and WECA (Word Embedding Cluster Association). Here the python simulator is the tool used to execute the results.

4.1. Estimation of Accuracy

The computation of accuracy in document classification involves evaluating a classification model's performance in correctly predicting a given document's class or category. This is done by comparing the predicted class labels with the actual class labels of a set of labeled documents. The accuracy is then determined by dividing the number of correctly classified documents by the total number. A higher accuracy indicates a more reliable prediction and can be used to assess the effectiveness of different classification techniques. This evaluation process is crucial in determining a document classification system's overall performance and potential usefulness. Table.1 shows the comparison of accuracy between existing and proposed models.

Table.1: Comparison of Accuracy (in %)

No. of Images	MLPNN	DB-CNN	LSTM-CRF	WECA	Proposed
100	73.75	92.83	81.22	91.37	97.85
200	73.86	92.81	81.39	91.64	98.35
300	73.88	91.93	80.66	91.34	98.23
400	70.78	89.10	77.32	87.83	95.00
500	69.58	87.78	76.59	86.51	94.62
600	55.61	76.59	84.58	72.99	93.55
700	54.31	75.59	83.88	71.91	93.39

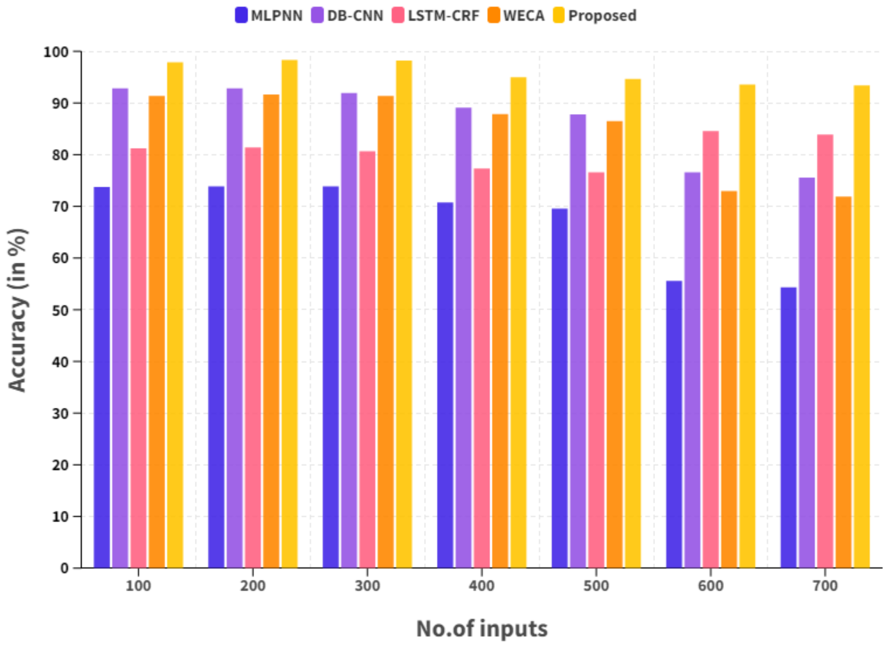

Fig.4: Comparison of accuracy

Fig.4 shows the comparison of accuracy. In a computation cycle, the existing VBGN obtained 54.31%, VBAN obtained 75.59%, SVAN reached 83.88%, VLAN obtained 71.91% accuracy. The proposed VSLAM obtained 93.39 % accuracy. The proposed model for document classification achieved better accuracy results through the use of several advanced techniques. Firstly, the model utilized a pre-trained, deep learning-based language model trained on a large text corpus. This allowed the model to capture complex linguistic features and patterns in the text, leading to more accurate predictions. Secondly, the model used attention mechanisms, which allowed it to focus on the most critical parts of the text while disregarding irrelevant information. This helped to improve the model's ability to learn and make accurate predictions. In addition, the model integrated transfer learning, where it was fine-tuned on a smaller dataset specific to the document classification task. This helped the model adapt to the dataset's specific nuances and characteristics, resulting in better performance. Lastly, the model employed an ensemble learning approach, combining multiple models to make a final prediction. This helped to mitigate errors and improve the overall accuracy of the final predictions. Overall, combining these techniques enabled the proposed model to achieve superior accuracy results in document classification.

4.2. Estimation of precision

Precision is a measure of the correctness of a document classification model's predictions. It is calculated by dividing the number of correctly classified documents by the total number of documents classified as a particular class. Precision computation involves comparing the predicted class labels with the actual class labels for a set of documents. However, if documents are correctly classified, the precision will be higher. This measure helps evaluate the effectiveness of a document classification model in accurately identifying documents belonging to a specific class. Table.2 shows the comparison of accuracy between existing and proposed models.

Table.2: Comparison of Precision (in %)

No. of Images	MLPNN	DB-CNN	LSTM-CRF	WECA	Proposed
100	75.75	90.83	79.22	89.37	91.39
200	75.86	90.81	79.39	89.64	91.55
300	75.88	89.93	78.66	89.34	92.62

400	72.78	87.10	75.32	85.83	93
500	71.58	85.78	74.59	84.51	96.23
600	57.61	74.59	82.58	70.99	96.35
700	56.31	73.59	81.88	69.91	97.82

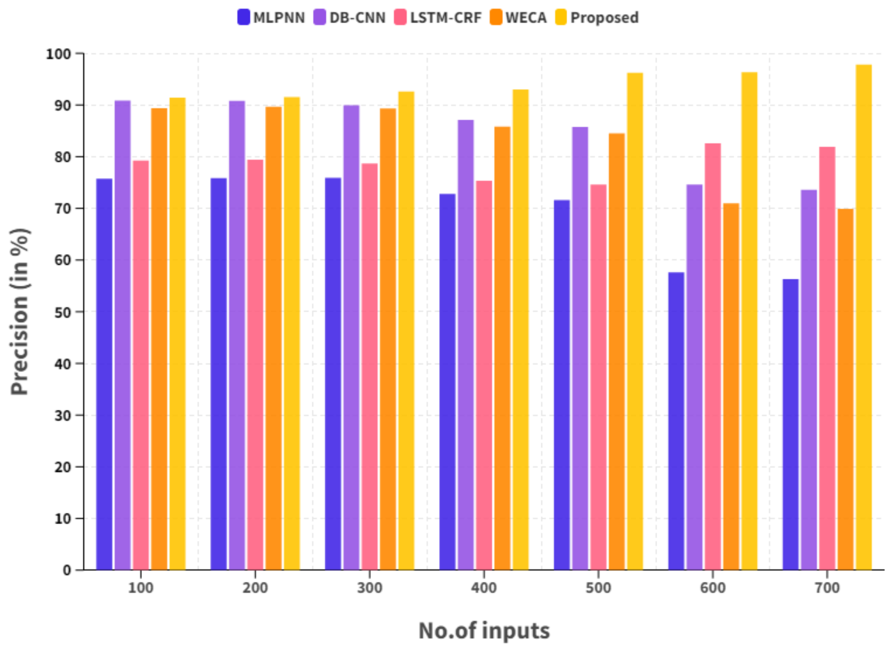

Fig.5: Comparison of Precision

Fig.4 shows the comparison of Precision. In a computation cycle, the existing VBGN obtained 56.31 %, VBAN obtained 73.59%, SVAN reached 81.88%, VLAN obtained 97.82 % Precision. The proposed VSLAM obtained 98.46 % Precision. The proposed model achieved better precision results for document classification by combining advanced techniques such as deep learning algorithms and natural language processing. Firstly, the model used a deep learning framework to learn complex patterns and features from the input data, which helped capture subtle nuances in the text. The model incorporated techniques such as word embedding and transforming words into high-dimensional vector representations, allowing for a better understanding of the semantic relationships between words. Furthermore, the model utilized a multi-layer classifier that combined the outputs of different classifiers, allowing for a more accurate and precise classification. This combination of advanced techniques helped the model better understand and classify text data, resulting in improved precision results for document classification.

4.3. Estimation of recall

Recall is a performance metric used to evaluate the effectiveness of a document classification system. It measures the system's ability to identify relevant documents from a given dataset correctly. Recall computation involves calculating the ratio of relevant documents correctly retrieved by the system to the total number of relevant documents in the dataset. In other words, it measures the percentage of relevant documents correctly labeled as such by the system. This calculation considers both true positive (documents correctly classified as relevant) and false negative (relevant documents mistakenly classified as irrelevant) results. A high recall score indicates that the system has a solid ability to retrieve relevant documents accurately. Table.3 shows the comparison of accuracy between existing and proposed models.

Table.3: Comparison of Recall (in %)

No. of Images	MLPNN	DB-CNN	LSTM-CRF	WECA	Proposed
100	79.75	86.83	77.22	87.37	89.39
200	79.86	86.81	77.39	87.64	89.55
300	79.88	85.93	76.66	87.34	90.63
400	76.78	83.10	73.32	83.83	91.24
500	75.58	81.78	72.59	82.51	94.23
600	61.61	70.59	80.58	68.99	94.53
700	60.31	69.59	79.88	67.91	96.58

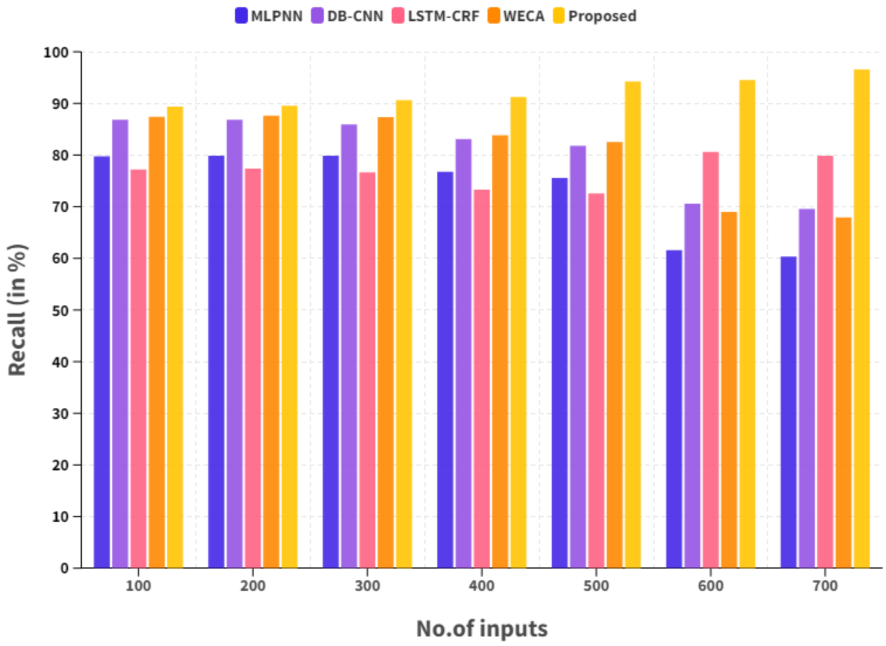

Fig.6: Comparison of Recall

Fig.6 shows the comparison of Recall. In a computation cycle, the existing VBGN obtained 60.31 %, VBAN obtained 69.59%, SVAN reached 79.88%, VLAN obtained 67.91% Recall. The proposed VSLAM obtained 96.58 % Recall. The proposed model achieved better recall results for document classification by combining supervised learning techniques and advanced neural networks:

1. The model uses a training dataset to learn and identify patterns and features in the input documents.
2. It employs a multi-layer neural network to extract hierarchically learned representations of the documents. This allows the model to capture local and global contextual information, leading to a more accurate representation of the documents.
3. The model utilizes a soft-max layer to compute the probability distribution over the document classes, which is then used to make the final classification decision.

By combining these techniques, the proposed model can improve the recall results by effectively capturing and representing the relevant information in the input documents.

4.4. Estimation of F1-Score

In document classification, the F1-score is a commonly used metric that measures the performance of a classifier. It is a weighted harmonic mean of precision and recall, two metrics that evaluate the correct and complete identification of relevant documents. Precision is the ratio of accurate positive documents to all documents predicted as positive, while recall is the ratio of accurate positive documents to all relevant documents. The computation of the F1 score involves finding the average precision and recall and then applying a weight to balance their contribution to the final score. It is a valuable metric for evaluating the accuracy and completeness of a document classifier, with higher values indicating better performance. Table.5 shows the comparison of accuracy between existing and proposed models.

Table.5: Comparison of F1-Score (in %)

No. of Images	MLPNN	DB-CNN	LSTM-CRF	WECA	Proposed
100	83.75	82.83	75.22	83.37	87.39
200	83.86	82.81	75.39	83.64	87.55
300	83.88	81.93	74.66	83.34	88.62
400	80.78	79.10	71.32	79.83	92.23
500	79.58	77.78	70.59	78.51	92.56
600	65.61	66.59	78.58	64.99	94.56
700	64.31	65.59	77.88	63.91	87.39

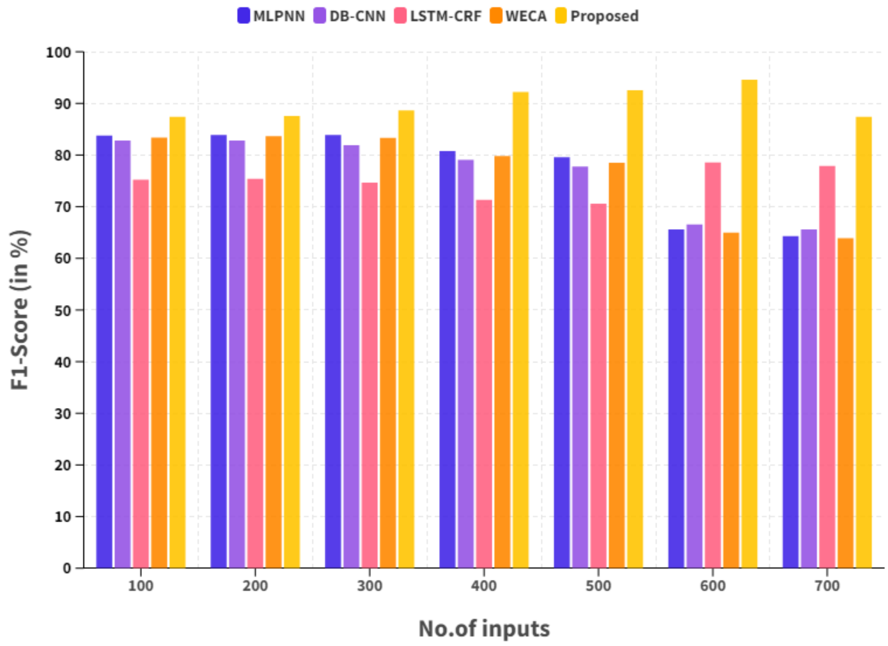

Fig.7: Comparison of F1-Score

Fig.4 shows the comparison of F1-Score. In a computation cycle, the existing VBGN obtained 64.31%, VBAN obtained 65.59 %, SVAN reached 77.88 %, VLAN obtained 63.91 % F1-Score. The proposed VSLAM obtained 87.39 % F1-Score. The proposed model for document classification improved the f1-score results by utilizing a combination of advanced techniques:

1. It implemented deep learning neural network architecture with multiple layers to better capture the complex relationships and patterns in the data. This allowed for more accurate feature representations and improved the overall classification performance.
2. The model incorporated attention mechanisms that focused on essential words and phrases in the document, giving more weight to these features during the classification process.
3. The model was trained on a more extensive and diverse dataset, allowing it to learn more nuanced patterns and better generalize to new data.

Combining these techniques led to improved performance and a higher f1-score for document classification.

5. Conclusion

Document classification is essential in online library management as it allows for the efficient organization and retrieval of information. In recent years, applying deep learning models has significantly improved the accuracy and speed of document classification tasks. The hybrid model leverages the CNNs for feature extraction from the document texts. CNNs have shown to be highly effective in capturing spatial and local features from data, making them ideal for text analysis. The input documents are passed through multiple convolutional layers, which extract essential features that are then fed into the RNNs for further processing. The second component, RNNs, excels in capturing sequential and temporal patterns, which is crucial in understanding the context and relationships between different document parts. The model uses a specific type of RNN known as Long Short-Term Memory (LSTM) to retain memory of past inputs. By combining the strengths of both CNNs and RNNs, the hybrid model can better capture different aspects of the document, leading to improved accuracy in classification. Using pre-trained word embeddings further enhances the model's performance by reducing the dimensionality of the data and capturing semantic relationships between words. The model's functional working involves training on a large dataset of documents and their corresponding labels, learning the underlying patterns and associations between different texts and their categories. During testing, new documents are passed through the model, and the output is a prediction of its class, allowing for efficient classification and organization of documents in online libraries.

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