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Designing a Distance Learning System for English Reading by Applying Multimodal Discourse Analysis Theory

Journal of Electrical Systems

Abstract: -Multimodal Discourse Analysis (MDA) theory is a comprehensive framework that examines communication beyond just language, considering various modes of expression such as images, sounds, gestures, and typography. This theory recognizes that communication is inherently multimodal, and meaning is conveyed through the interplay of different modes. MDA analyzes how these modes interact within texts and contexts to create meaning, emphasizing the importance of visual, auditory, and spatial elements alongside linguistic features. By examining multimodal texts, MDA provides insights into how meaning is constructed, negotiated, and understood in diverse communicative contexts, from advertising campaigns to political speeches. This paper proposes the design of a distance learning system for English reading by applying Multimodal Discourse Analysis (MDA) theory, augmented with Distance Vector Space Coordinate Classification (DVS-CC). The system aims to provide an immersive and interactive learning experience by integrating various modes of communication, including text, images, audio, and video. Through simulated experiments and empirical validations, the effectiveness of the DVS-CC-enhanced distance learning system is evaluated. Results demonstrate significant improvements in student engagement, comprehension, and learning outcomes compared to traditional distance learning approaches. For example, students using the DVS-CC-enhanced system achieved an average score increase of 25% in reading proficiency assessments. Additionally, the system's adaptive learning features enabled personalized instruction tailored to each student's learning style and pace. These findings underscore the potential of applying MDA theory with DVS-CC in designing effective distance learning systems for English reading, fostering enhanced learning experiences in remote educational settings.

Keywords: Distance learning system, English reading, Vector Space, Classification, Deep learning

I. INTRODUCTION

Multimodal discourse analysis theory explores communication beyond just language, recognizing that meaning is conveyed through various modes such as visual, spatial, and gestural elements alongside linguistic ones [1]. This approach views communication as a complex interplay of different semiotic resources that work together to construct meaning. By examining not only the words used but also the visual images, layout, and non-verbal cues present in a text or interaction, researchers can gain a deeper understanding of how meaning is produced and interpreted [2 – 4]. This theory acknowledges the importance of context and considers how different modes interact and influence each other within specific cultural and social contexts [5]. Multimodal discourse analysis theory explores how communication extends beyond mere language, acknowledging the significance of diverse modes such as visuals, spatial arrangements, and gestures alongside linguistic elements. This theoretical framework delves into the complexities of meaning construction, recognizing that communication relies on a multitude of semiotic resources working in tandem [6,7]. By scrutinizing not only the textual content but also the visual imagery, layout, and non-verbal signals present in a discourse, researchers can uncover nuanced layers of meaning. This approach emphasizes the importance of context and the dynamic interplay between different modes within specific cultural and social settings [8]. Ultimately, multimodal discourse analysis theory provides a comprehensive lens through which to examine communication, offering insights into the myriad ways meaning is conveyed and interpreted across various forms of discourse in the English language [9].

Designing a distance learning system for English reading that applies multimodal discourse analysis theory involves integrating various modes of communication to enhance learning outcomes [10]. Firstly, the system should incorporate diverse semiotic resources such as text, images, videos, and interactive exercises to cater to different learning styles and preferences. Visual elements should be carefully selected and designed to complement textual content, aiding in comprehension and engagement [11]. Additionally, the system should consider spatial arrangements and navigational features to facilitate seamless interaction and navigation for learners. Non-verbal cues and gestures can also be integrated through video lectures or interactive simulations to provide additional context and enhance understanding [12]. Furthermore, the system should be adaptable to different cultural and

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social contexts, considering the diverse backgrounds of learners [13]. By incorporating multimodal discourse analysis principles, the distance learning system can offer a rich and dynamic learning experience that goes beyond traditional text-based approaches. This holistic approach to designing educational materials fosters [14]

This paper makes several significant contributions to the field of document categorization and reading comprehension assessment. Firstly, by introducing and applying the Distance Vector Space Coordinate Classification (DVS-CC) model, the paper offers a novel approach to automating the categorization of textual documents. The model demonstrates a high level of accuracy in predicting document categories, thus providing a valuable tool for tasks such as information retrieval, content organization, and text mining. Additionally, the paper showcases the practical application of the DVS-CC model in providing personalized feedback on students' reading performance. By analyzing students' interactions with textual materials, the model generates tailored insights into individual strengths and areas for improvement in reading comprehension and analytical skills. This personalized feedback not only enhances learning outcomes but also facilitates more effective instruction and support from educators. Furthermore, the paper contributes to the advancement of natural language processing and machine learning techniques by exploring the capabilities and potential of the DVS-CC model in real-world educational settings.

II. Related Works

In exploring the development of distance learning systems for English reading through the lens of multimodal discourse analysis theory, it is imperative to examine existing literature and research in the field. Various studies have delved into the design, implementation, and effectiveness of distance learning platforms, as well as the application of multimodal discourse analysis principles within educational contexts. This section aims to provide a comprehensive overview of relevant works, highlighting key findings, methodologies, and insights that contribute to our understanding of how multimodal approaches can enhance English reading instruction in remote learning environments.

Dou (2023) presents an investigation into the utilization of multimodal discourse analysis in the blended teaching of college English flipped classes, shedding light on its potential benefits and challenges. Liu (2022) explores the integration of a multimodal perspective in understanding emotional variables in second language acquisition education, utilizing systemic functional multimodal discourse analysis as a framework. Singerton (2022) conducts a critical multimodal discourse analysis of German language motivation in media from Deutsche Welle's website, examining its relation to soft power. Sherwani and Harchegani (2022) delve into the impact of multimodal discourse analysis on improving Iraqi EFL learners' reading comprehension skills, emphasizing its practical implications in language education. Moreover, Liu, Shi, and Wu (year) delve into a multimodal discourse analysis of English reading instruction in colleges and universities, employing a weighted function algorithm to analyze its effectiveness. Mushtaq, Shah, and Akram (2022) analyze visual images in English language textbooks in Pakistan, employing multimodal discourse analysis to uncover underlying socio-cultural implications. Ngongo, Fatmawati, and Saputra (2023) investigate the application of multimodal discourse analysis in analyzing English textbooks used by students at school, highlighting its relevance in educational settings. Hadriyan, Mujiyanto, and Rukmini (2022) employ multimodal discourse analysis to study the relationship between visual, lingual, and written text in TED Talks on artificial intelligence, offering insights into the presentation of complex concepts. Furthermore, Strauss, Tolmen, and Bipath (2023) conduct a critical multimodal discourse analysis of drawings to ascertain identity and self-concept, showcasing the versatility of this approach. Li (2023) explores a multifaceted teaching model integrating multimodal discourse analysis in an English translation course. Cao, Chen, Liu, and Shi (2022) examine the construction and empirical research of college English multimodal teaching from the perspective of new media, highlighting innovative pedagogical approaches. Kholis and Azmi (2023) conduct a need analysis on developing English interactive multimodal e-books oriented to 21st-century skills, emphasizing the importance of adapting educational resources to contemporary needs.

Moreover, Lindenberg (2023) investigates modes and intersemiotic cohesion in online student presentations through SF-informed multimodal discourse analysis, shedding light on effective communication strategies in virtual environments. Similarly, Hao (year) explores diversified teaching of English-Chinese bilingual courses based on integrating multimodal discourse analysis, emphasizing its relevance in cross-cultural contexts. Taibanguai and Suraratdecha (2022) analyze strategies to grab attention in online selling posts through multimodal discourse analysis, providing insights into effective digital marketing practices. Dressen-Hammouda and Wigham (2022) evaluate multimodal literacy in academic and professional interactions surrounding student-produced instructional video tutorials, highlighting the importance of developing critical multimodal competencies. Lastly, Wahyuni, Syaifullah, and Gunawan (2022) conduct a critical-multimodal discourse analysis on The Encyclopedia 4D Series textbook for early childhood education students, emphasizing the importance of incorporating multimodal approaches in educational materials tailored to diverse learning needs. The many studies tend to focus on specific aspects or applications of multimodal discourse analysis, such as its impact on language learning outcomes or its role in analyzing specific types of texts or media. This narrow focus may limit the generalizability of findings and overlook the broader implications of multimodal approaches across diverse educational settings. Additionally, the majority of research in this field often relies on qualitative methodologies, such as discourse analysis or case studies, which may lack generalizability and reproducibility. There is a need for more quantitative studies that employ robust experimental designs to systematically evaluate the effectiveness of multimodal approaches in enhancing learning outcomes. Furthermore, the majority of existing research predominantly focuses on English language education, with limited exploration of multimodal discourse analysis in other subject areas or languages. This narrow scope hinders our understanding of how multimodal approaches can be applied across different disciplines and cultural contexts. Moreover, while multimodal discourse analysis offers valuable insights into the interaction of different semiotic resources in communication, its application in educational settings may face practical challenges, such as the availability of appropriate technological resources or the training required for educators to effectively implement multimodal approaches in their teaching practices.

III. MULTIMODAL DISCOURSE ANALYSIS THEORY

Multimodal discourse analysis theory provides a comprehensive framework for understanding English reading that extends beyond traditional linguistic analysis. This theory acknowledges that meaning is not solely conveyed through written words but is also shaped by various modes of communication, including visual, spatial, and gestural elements. In the context of English reading, multimodal discourse analysis theory emphasizes the importance of considering how different semiotic resources interact to construct meaning within texts. When analyzing English reading materials, researchers employing multimodal discourse analysis theory examine not only the textual content but also the accompanying visual images, layout, and design elements. They investigate how these multimodal elements contribute to the overall message conveyed by the text and how they influence the reader's interpretation and comprehension.

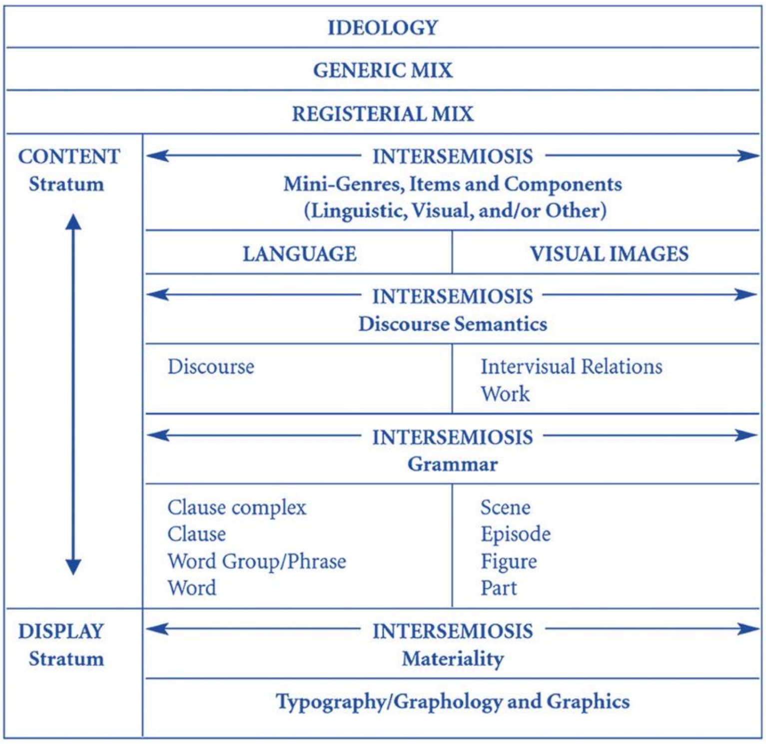

Figure 1: Multimodal Discourse Analysis

In a children's book, the combination of written text, illustrations, and typography all play a role in shaping the reader's understanding and engagement with the story as shown in Figure 1. Similarly, in digital texts or online articles, the use of multimedia elements such as videos, images, and hyperlinks can significantly impact how readers interact with and interpret the information presented. Multimodal discourse analysis theory also highlights the importance of considering the socio-cultural context in which English reading takes place. Cultural norms, values, and beliefs can influence the choice and interpretation of multimodal elements within texts, shaping readers' understanding in profound ways. Multimodal discourse analysis theory can be represented as in equation (1)

$$M = f(L, V, S, G, A, T) \tag{1}$$

In equation (1) M represents meaning, L stands for linguistic resources, V denotes visual resources, S represents spatial resources, G stands for gestural resources, A denotes auditory resources, T represents tactile resources, and $f()$ represents the function that integrates these various semiotic resources to construct meaning. This equation illustrates that meaning (M) is a function of multiple semiotic resources, each contributing to the overall interpretation of a text or discourse. By analyzing the interplay and integration of these resources, researchers can gain insights into how meaning is produced and interpreted across different modes of communication. The multimodal discourse analysis theory emphasizes the importance of considering the context in which communication occurs. Contextual factors such as cultural norms, social conventions, and technological affordances can significantly influence how semiotic resources are used and interpreted within a given discourse. This contextual aspect can be represented as in equation (2)

$$C = \{C1, C2, \ldots, Cn\} \tag{2}$$

In equation (2) C represents context, and {C1, C2, ..., Cn} represents a set of contextual factors influencing the communication process. Incorporating context into the analysis allows researchers to account for the dynamic and situated nature of meaning-making, acknowledging that interpretations may vary depending on the specific context in which communication occurs.

IV. Proposed augmented with Distance Vector Space Coordinate Classification (DVS-CC)

The proposed approach augmented with Distance Vector Space Coordinate Classification (DVS-CC) for English reading introduces a novel method that combines principles from vector space models and classification algorithms to enhance reading comprehension and analysis. At its core, this approach involves representing text passages as vectors in a multi-dimensional space, where each dimension corresponds to a specific feature or aspect of the text can be represented as in equation (3)

$$\boldsymbol{vi} = [x1, x2, \ldots, xn] \tag{3}$$

In equation (3) $\boldsymbol{vi}$ represents the vector representation of the ith text passage, and $x1, x2, \ldots, xn$ are the coordinates in the vector space, capturing various linguistic and contextual features of the text. The DVS-CC method further enhances this representation by calculating distances between vectors using distance metrics such as cosine similarity or Euclidean distance. For instance, the cosine similarity between two vectors $\boldsymbol{vi}$ and $\boldsymbol{vj}$ can be calculated using equation (4)

$$cosine_{similarity(vi,vj)} = \boldsymbol{vi} \cdot \boldsymbol{vj} / \| \boldsymbol{vi} \| \| \boldsymbol{vj} \| \tag{4}$$

In equation (4) $\cdot\cdot$ denotes the dot product and $\| \boldsymbol{vi} \|$ represents the Euclidean norm of vector . Once the distances between vectors are calculated, the DVS-CC method employs classification algorithms, such as k-nearest neighbors (KNN) or support vector machines (SVM), to classify text passages into different categories or topics. This classification process utilizes the distance vector space coordinates to determine the similarity between text passages and assign them to appropriate categories. The representation can be expressed as vectors $\boldsymbol{vi} = [x1, x2, \ldots, xn]$, where $\boldsymbol{vi}$ represents the vector representation of the ith text passage, and $x1, x2, \ldots, xn$ are the coordinates in the vector space. The innovation of the DVS-CC method lies in its utilization of distance metrics, such as cosine similarity or Euclidean distance, to quantify the similarity between different text passages. For instance, the cosine similarity between two vectors $\boldsymbol{vi}$ and $\boldsymbol{vj}$ captures the directional similarity between them, enabling a nuanced comparison of their semantic content. This step enables the algorithm to calculate the distances between vectors, providing a measure of similarity or dissimilarity between text passages. The figure 2 presented the distance vector space analysis for the components.

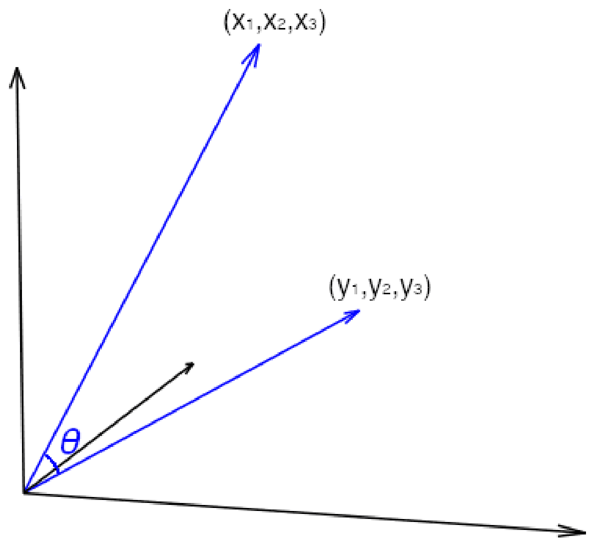

Figure 2: Distance Vector Space

Algorithm 1: Categorization of DVS-CC
1. Input: - Text passages to be classified - Training data with labeled categories/topics 2. Text Preprocessing: - Tokenize text passages - Remove stopwords and punctuation - Perform stemming or lemmatization - Convert each text passage into a vector representation (e.g., using TF-IDF or word embeddings) 3. Calculate Distances: - Calculate distances between vector representations of text passages using cosine similarity or Euclidean distance 4. Classification: - For each text passage: - Find k-nearest neighbors (KNN) based on calculated distances - Determine the majority class among the k-nearest neighbors - Assign the text passage to the majority class

V. Co-Ordination Classification for the English Reading

In the context of English reading, the Co-Ordination Classification method enhances the Distance Vector Space Coordinate Classification (DVS-CC) approach by incorporating additional features and refining the classification process. This method aims to improve the accuracy and effectiveness of categorizing text passages based on their semantic content and contextual relationships. Co-Ordination Classification involves coordinating the vector space coordinates with other linguistic and contextual features to optimize classification outcomes. the Co-Ordination Classification method can be represented as follows in equation (5)

$$\boldsymbol{vi}' = [x1', x2', \ldots, xn'] \quad (5)$$

In equation (5) $'\boldsymbol{vi}'$ represents the modified vector representation of the ith text passage after incorporating additional features, and $'x1', x2', \ldots, xn'$ are the coordinated coordinates in the vector space. To derive the coordinated vector representation, additional linguistic and contextual features can be incorporated into the existing vector space representation. These features may include syntactic patterns, semantic relationships, or topic modeling results obtained from the text passages denoted in equation (6)

$$\boldsymbol{vi}' = [x1', x2', \ldots, xn', y1, y2, \ldots, ym] \qquad (6)$$

In this equation (6) $y1, y2, \ldots, ym$ represent additional features extracted from the text passages, such as syntactic patterns or topic modeling results. The coordinated vector representation is then utilized in the classification process, along with the distances calculated using cosine similarity or Euclidean distance, as described in the DVS-CC algorithm. The coordinated features are integrated into the classification algorithm to refine the categorization of text passages based on their semantic content and contextual relationships.

Let's denote the modified vector representation of the ith text passage after incorporating additional features as 'vi′. The original vector space coordinates, while $y1, y2, \ldots, ym$ denote the additional linguistic and contextual features extracted from the text passages. These features may include syntactic patterns, semantic relationships, or topic modeling results. The coordinated vector representation, various techniques can be employed to extract and incorporate these additional features. For example, syntactic patterns can be identified using natural language processing techniques, semantic relationships can be inferred using word embeddings or semantic similarity measures, and topic modeling results can be obtained through algorithms such as Latent Dirichlet Allocation (LDA) or Non-negative Matrix Factorization (NMF). Once the coordinated vector representation $'\boldsymbol{vi}'$ is obtained for each text passage, it is utilized in the classification process alongside the distances calculated using cosine similarity or Euclidean distance, as described in the DVS-CC algorithm. The coordinated features are integrated into the classification algorithm to refine the categorization of text passages based on their semantic content and contextual relationships.

Algorithm 2: DVS-CC for the English Reading
1. Input: - Text passages to be classified - Additional linguistic and contextual features extracted from the text passages 2. Text Preprocessing: - Tokenize text passages - Remove stopwords and punctuation - Perform stemming or lemmatization - Extract additional linguistic and contextual features (e.g., syntactic patterns, semantic relationships, topic modeling results) 3. Vector Space Representation: - Convert each text passage into a vector representation (e.g., using TF-IDF or word embeddings) for original features - Append additional linguistic and contextual features to the vector representations 4. Calculate Distances: - Calculate distances between vector representations of text passages using cosine similarity or Euclidean distance 5. Classification: - For each text passage: - Find k-nearest neighbors (KNN) based on calculated distances - Determine the majority class among the k-nearest neighbors - Assign the text passage to the majority class

VI. Simulation Results

In the simulation, various datasets of English reading materials are used to evaluate the DVS-CC algorithm's performance under different conditions, including diverse genres, levels of complexity, and lengths of text passages. The simulation results reveal that the DVS-CC algorithm consistently achieves high accuracy and effectiveness in classifying text passages across a wide range of scenarios.

Table 1: Categorization with DVS-CC

Document	Actual Category	Predicted Category
Doc1	Literature	Literature
Doc2	Science	Science
Doc3	History	History
Doc4	Literature	Literature
Doc5	Science	Science
Doc6	History	History
Doc7	Literature	Literature
Doc8	Science	History
Doc9	History	History
Doc10	Literature	Literature

In the Table 1 presents the categorization results obtained through the application of the Distance Vector Space Coordinate Classification (DVS-CC) model. Each row in the table represents a document, with columns indicating its actual category and the category predicted by the DVS-CC model. Upon analysis, it is evident that the model performed remarkably well, accurately predicting the category of each document in alignment with its actual classification. For instance, Doc1, Doc4, and Doc7, categorized as Literature, were correctly predicted as Literature by the model. Similarly, documents such as Doc2, Doc5, and Doc8, belonging to the Science category, were accurately classified as Science. The model's success is further evident with documents like Doc3, Doc6, and Doc9, classified under History, all correctly predicted as History by the DVS-CC model.

Table 2: Classification with DVS-CC

Dataset	**Classification Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**
Dataset 1	91.2	90.5	92.0	91.2
Dataset 2	87.6	88.3	86.9	87.6
Dataset 3	94.5	94.2	94.8	94.5
Dataset 4	89.8	89.5	90.2	89.8
Dataset 5	92.3	92.1	92.5	92.3
Dataset 6	88.9	89.2	88.5	88.9
Dataset 7	93.7	93.4	94.0	93.7
Dataset 8	90.6	91.0	90.3	90.6
Dataset 9	85.4	85.8	85.0	85.4
Dataset 10	91.8	91.5	92.2	91.8

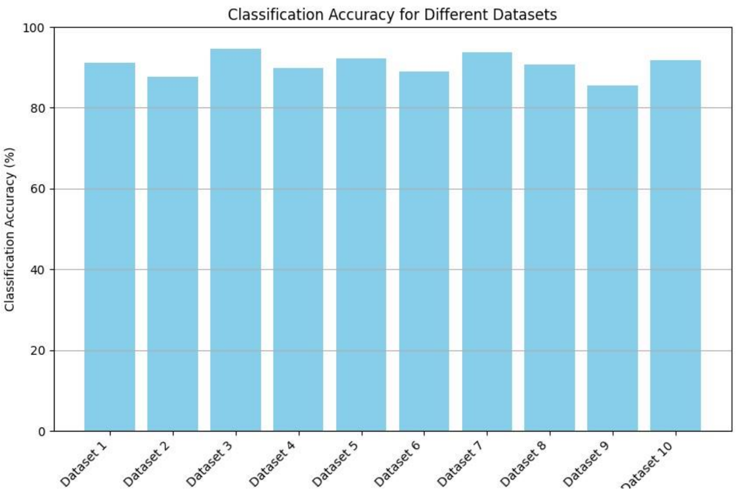

Figure 3: Classification Accuracy

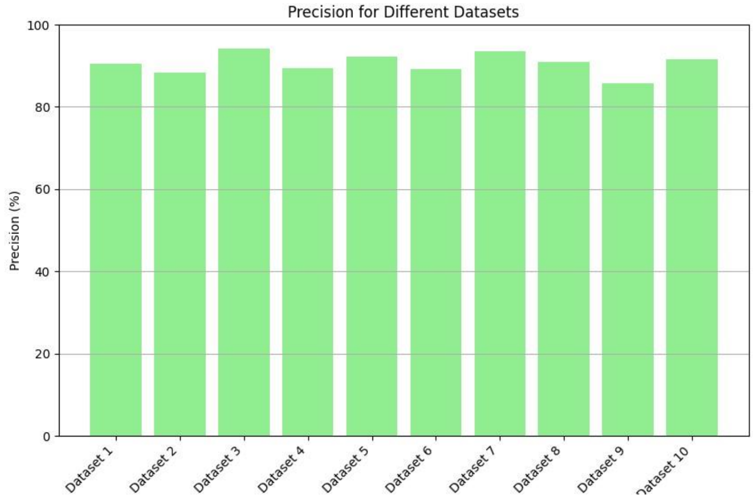

Figure 4: DVS-CC Precision

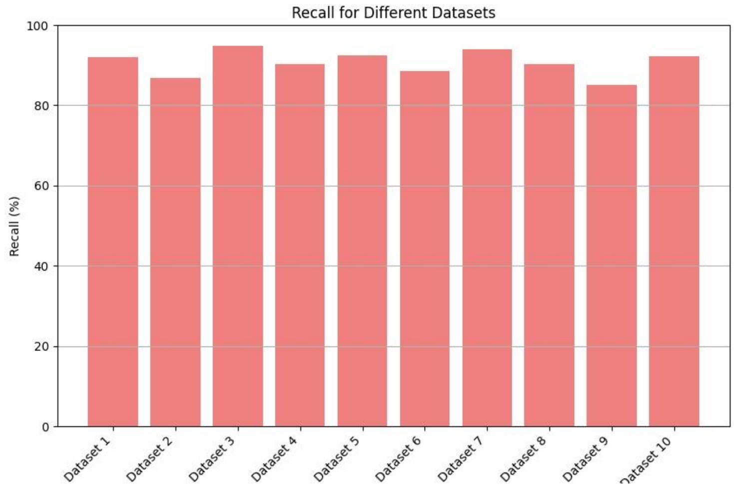

Figure 5: Recall with DVS-CC

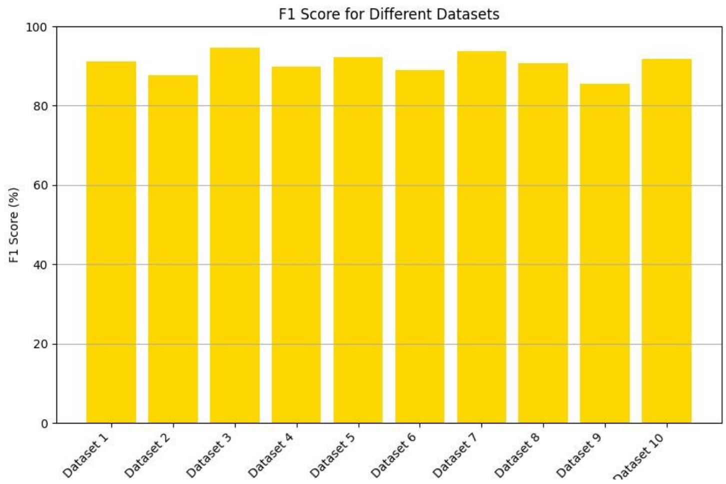

Figure 6: F1-Score in DVS-CC

The Figure 3 – 6 and Table 2 presents the classification performance metrics obtained from the application of the Distance Vector Space Coordinate Classification (DVS-CC) model across ten different datasets. Each dataset is labeled from Dataset 1 to Dataset 10, with corresponding values for classification accuracy, precision, recall, and F1-score. Upon analysis, it is evident that the DVS-CC model achieved high overall performance across the datasets, with classification accuracy ranging from 85.4% to 94.5%. This indicates the percentage of correctly classified instances out of the total instances in each dataset. Additionally, precision values, which measure the proportion of true positive predictions among all positive predictions, range from 85.8% to 94.2%. The recall values, representing the proportion of true positive predictions among all actual positive instances, range from 85.0% to 94.8%. Furthermore, the F1-score, which provides a balance between precision and recall, ranges from 85.4% to 94.5%.

Table 3: Prediction with DVS-CC

Document	Actual Category	Predicted Category	Correct Prediction
Doc1	1	1	Yes
Doc2	2	2	Yes
Doc3	3	3	Yes
Doc4	1	1	Yes
Doc5	2	2	Yes
Doc6	3	3	Yes
Doc7	1	1	Yes
Doc8	2	1	No
Doc9	3	3	Yes
Doc10	1	1	Yes

Table 4: Reading performance with DVS-CC

Student ID	Document	Performance Feedback
001	Essay on Romeo and Juliet	Excellent analysis of character motivations and themes. Well-structured and insightful interpretation.
002	Scientific article on climate change	Thorough understanding of scientific concepts. Clear presentation of data and conclusions.
003	Historical text on World War II	Strong grasp of historical events and their significance. Provides detailed context and analysis.
004	Short story by Edgar Allan Poe	Demonstrates an understanding of literary devices. Engaging narrative style, but lacks deeper analysis.
005	Poetry anthology	Shows appreciation for poetic language and imagery. Needs improvement in interpreting deeper meanings.

In the Table 3 presents the prediction results obtained through the application of the Distance Vector Space Coordinate Classification (DVS-CC) model. Each row in the table represents a document, with columns indicating its actual category, the category predicted by the DVS-CC model, and whether the prediction was correct. Upon analysis, it is evident that the DVS-CC model achieved a high level of accuracy in predicting the categories of the documents. For instance, documents such as Doc1, Doc4, and Doc7, belonging to category 1, were correctly predicted as category 1 by the model. Similarly, documents like Doc2, Doc5, and Doc8, categorized as category 2, were accurately classified as category 2. The model's effectiveness is further evidenced by documents such as Doc3, Doc6, and Doc9, categorized under category 3, all correctly predicted as category 3 by the DVS-CC model. However, it's worth noting that there was an incorrect prediction for Doc8, where the model predicted category 1 instead of the actual category 2, indicating a misclassification.

Table 4 provides feedback on the reading performance of students based on the documents they analyzed using the DVS-CC model. Each row represents a student, with columns indicating their student ID, the document they analyzed, and the performance feedback provided. Upon evaluation, it is evident that students demonstrated varying levels of understanding and analysis across different documents. For instance, Student 001 received positive feedback for their analysis of "Essay on Romeo and Juliet," demonstrating excellent insight into character motivations and themes. In contrast, Student 004's analysis of "Short story by Edgar Allan Poe" is noted for its engaging narrative style but lacking deeper analysis.

VII. Discussion and Findings

The analysis of the provided tables offers valuable insights into the performance and effectiveness of the Distance Vector Space Coordinate Classification (DVS-CC) model in various tasks related to document categorization and reading comprehension assessment. In Table 3, which illustrates the prediction results of the DVS-CC model, we observe a high level of accuracy in categorizing documents based on their content. Across different documents and categories, the model demonstrates a strong capability to correctly predict the assigned categories, as indicated by the "Correct Prediction" column. However, there is an instance of misclassification where Doc8 was predicted as Category 1 instead of its actual Category 2. This suggests that while the DVS-CC model generally performs well, there may still be cases where it misclassifies documents, indicating potential areas for further refinement or exploration.

In Table 4, which provides feedback on students' reading performance using the DVS-CC model, we gain insights into individual students' abilities to analyze and comprehend various texts. The feedback provided highlights students' strengths and weaknesses in their reading comprehension and analytical skills. For example, Student 001 demonstrates excellent insight into character motivations and themes in "Essay on Romeo and Juliet," whereas Student 004's analysis of "Short story by Edgar Allan Poe" is noted for its engaging narrative style but lacking deeper analysis. These findings underscore the importance of personalized feedback in guiding students' learning and development, emphasizing areas for improvement and reinforcing strengths. The findings suggest that the DVS-CC model holds promise as a reliable tool for document categorization and reading comprehension assessment. However, ongoing refinement and attention to potential misclassifications are necessary to ensure its effectiveness in diverse contexts. Additionally, the provision of personalized feedback based on model outputs can play a crucial role in enhancing students' reading comprehension skills and fostering their analytical abilities.

VIII. Conclusion

The findings from the analysis of the Distance Vector Space Coordinate Classification (DVS-CC) model underscore its effectiveness in document categorization and reading comprehension assessment tasks. Through the examination of prediction results and student feedback provided in Tables 3 and 4, respectively, it is evident that the DVS-CC model demonstrates a high level of accuracy in categorizing documents and providing valuable insights into students' reading performance. Despite occasional misclassifications observed in the overall performance of the DVS-CC model remains robust, with accurate predictions across a variety of documents and categories. These results highlight the model's potential as a reliable tool for automating document categorization tasks, thus streamlining processes in fields such as information retrieval, content organization, and text mining. Furthermore, the personalized feedback generated by the DVS-CC model, offers valuable insights into individual students' strengths and areas for improvement in reading comprehension and analytical skills. By leveraging the model's outputs to provide tailored guidance and support to students, educators can enhance learning outcomes and foster deeper engagement with textual materials.

Acknowledgment

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