



International Journal of Innovative Research in Science Engineering and Technology (IJIRSET)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)



Impact Factor: 8.699

Volume 14, Issue 4, April 2025

Automated Paper Correction using Machine Learning and Deep Learning

Mr. K. Sudhaakar, C Bhavitha, B Vasundara, C Rahul Kumar

Assistant professor, Dept. of CSE, Bharath Institute of Higher Education and Research, Selaiyur, Chennai,
Tamil Nadu, India

B-Tech Student, Dept. of CSE, Bharath Institute of Higher Education and Research, Selaiyur, Chennai,
Tamil Nadu, India

B-Tech Student, Dept. of CSE, Bharath Institute of Higher Education and Research, Selaiyur, Chennai,
Tamil Nadu, India

B-Tech Student, Dept. of CSE, Bharath Institute of Higher Education and Research, Selaiyur, Chennai,
Tamil Nadu, India

ABSTRACT: Automatic paper correction is a challenging task that requires understanding both textual content and contextual meaning. This project leverages Region-based Convolutional Neural Networks (RCNN) and Bidirectional Encoder Representations from Transformers (BERT) to build an efficient and intelligent paper evaluation system. The system supports text, PDF, and handwritten text, ensuring flexibility across various document formats. RCNN is employed for handwritten text recognition, extracting and converting handwritten content into digital text. Meanwhile, BERT is used for semantic analysis and error detection, ensuring deep contextual understanding for automated corrections. The Flask framework is used for deploying the model as a web application, allowing users to upload documents and receive real-time corrections and feedback. This solution aims to automate the grading process, reduce human effort, and improve accuracy in academic and professional settings. It provides an interactive interface, enabling users to review corrections efficiently. The integration of deep learning and NLP ensures that the system can understand and correct grammatical errors, semantic inconsistencies, and logical structuring in written content.

KEYWORDS: Image processing, CRNN, BERT Model, OCR, Cosine Similarities.

I. INTRODUCTION

Automating the process of paper correction has become increasingly important in the digital age. Traditional methods of evaluating written content require significant time and effort, making them inefficient for large-scale assessments. Our project, an Automated Paper Correction System, utilizes advanced deep learning models such as Region-based Convolutional Neural Networks (RCNN) and Bidirectional Encoder Representations from Transformers (BERT) to enhance accuracy and efficiency in document evaluation. By integrating these technologies, the system can analyse, correct, and provide feedback on various types of textual content, including typed documents, PDFs, and handwritten submissions. Manual paper correction often introduces subjectivity and inconsistency, which can lead to unfair grading and errors. Educators and professionals spend hours reviewing written material, which can result in fatigue and decreased accuracy. Automating this process reduces human bias and ensures a standardized approach to evaluating textual content. The implementation of RCNN for handwritten text recognition allows the system to extract content from scanned documents, converting handwritten text into a digital format for further analysis. Once digitized, BERT performs semantic analysis, identifying grammatical mistakes, contextual errors, and logical inconsistencies in the text. The integration of deep learning enhances the system's ability to understand the meaning of sentences rather than just checking for spelling and grammatical errors. Unlike conventional grammar checkers, which focus on rule-based corrections, BERT leverages contextual embeddings to determine the intended meaning behind words and phrases. This allows the system to provide more accurate and meaningful corrections, improving the overall quality of written content. The combination of RCNN and BERT ensures that both handwritten and typed documents undergo comprehensive evaluation, making the system suitable for a wide range of applications.

One of the key advantages of this system is its ability to handle multiple document formats. Users can upload text files, PDFs, and even images of handwritten documents, making it a versatile tool for academic and professional use. The conversion of handwritten text into a digital format is an essential step, as many students and professionals still rely on handwritten notes and exam papers. By accurately transcribing these documents, the system ensures that no valuable information is lost during the evaluation process to provide an interactive and user-friendly experience, the system is deployed as a web application using Flask. The web interface allows users to upload their documents, receive instant corrections, and review suggested changes. Real-time feedback is a crucial aspect of this system, as it enables students and professionals to improve their writing before final submissions. By receiving immediate insights into their errors, users can enhance their writing skills and develop a better understanding of grammar, sentence structure, and logical flow. The automation of paper correction significantly reduces the workload for educators, allowing them to focus on more critical aspects of teaching and mentoring. In academic institutions with large student populations, manually grading essays, research papers, and assignments can be overwhelming. The Automated Paper Correction System streamlines this process by providing consistent and accurate evaluations, ensuring fair grading for all students. This system also benefits professionals who need to review reports, legal documents, and business proposals, helping them maintain high-quality written communication. Ensuring fairness and accuracy in grading is a major challenge in manual paper correction. Human evaluators may have unconscious biases that affect their grading decisions, leading to inconsistencies in scores. The AI-driven approach minimizes these biases by applying the same evaluation criteria to all submissions. This results in a fairer assessment process, where every document is judged purely based on its content rather than subjective opinions. Additionally, the system can be trained on specific grading criteria, allowing customization for different academic and professional requirements. Despite its advantages, implementing an automated paper correction system comes with challenges. One of the primary difficulties is the variability in handwriting styles, which can make text recognition complex. RCNN addresses this issue by being trained on diverse datasets, enabling it to recognize a wide range of handwriting patterns. Another challenge is the detection of nuanced contextual errors, especially in long-form writing such as essays and reports. BERT's advanced language modelling capabilities help mitigate this by analysing entire sentence structures rather than just individual words.

II. SYSTEM MODEL

The workflow of an automated paper correction system involves multiple stages, from document input to final feedback generation. The process begins with the user uploading a document, which can be in the form of text, PDF, or handwritten content. The system needs to handle different file formats efficiently, ensuring smooth document processing regardless of its type. Once the document is uploaded, it undergoes an initial preprocessing step to improve text readability and extract meaningful content for further analysis. For handwritten documents, Region-based Convolutional Neural Networks (RCNN) are used for text extraction. The system first applies image processing techniques such as binarization, noise reduction, and contrast enhancement to refine the quality of the scanned document. These preprocessing steps help in reducing distortions and improving the recognition accuracy of handwritten text. The RCNN model then segments the document into regions and extracts text from each section, converting it into a digital format.



Fig 1: Design Architecture

After extracting the text, the system proceeds with structural analysis, where the format, paragraph organization, and sentence alignment are evaluated. This step ensures that the extracted content maintains its original structure and is correctly aligned with the intended formatting. Errors due to misalignment or missing words are identified at this stage, ensuring an accurate representation of the input document. Once the text is digitized, it is passed through an evaluation model that assesses grammatical correctness, spelling, and content coherence. The system detects common mistakes such as incorrect verb usage, misplaced punctuation, and redundant phrases. Advanced machine learning models are trained on large datasets to recognize complex patterns in text, allowing them to identify and correct errors efficiently. The next phase involves contextual assessment, where the system examines sentence flow and logical consistency. This ensures that the text follows a coherent structure and that sentences are well-connected. In academic and professional settings, maintaining logical progression in writing is essential, and this step helps improve overall content clarity. The system highlights areas where sentence transitions can be improved and suggests modifications to enhance readability. Simultaneously, for handwritten content, character recognition is refined by comparing extracted text with reference datasets. The model continuously learns from diverse handwriting samples, improving its ability to recognize different writing styles. Any misrecognized characters or words are flagged, and the system suggests possible corrections based on contextual understanding. The corrected text is then formatted and structured before being presented to the user. The system ensures that paragraph breaks, indentation, and alignment are preserved, maintaining the integrity of the original document. This step is crucial, especially when dealing with academic papers or professional reports that require strict formatting guidelines.

After formatting, a feedback generation module analyses the corrected content and provides suggestions to the user. The system categorizes errors based on severity, highlighting critical mistakes that need immediate attention while also suggesting minor improvements. This interactive feedback mechanism helps users understand their mistakes and refine their writing skills over time. The web application, built using Flask, facilitates user interaction by allowing seamless document uploads and real-time correction display. Users can view the corrected version of their document alongside the original text, making it easier to compare changes and implement improvements. The web interface is designed to be intuitive, ensuring accessibility for users across different domains. Once the user receives feedback, they have the option to accept or reject suggested corrections. This ensures that the final output aligns with their writing intent. The system also provides an option to download the corrected document in various formats, making it convenient for users to integrate the changes into their work. For large-scale applications, the system supports batch processing, where multiple documents can be uploaded and evaluated simultaneously. This feature is particularly useful for institutions that need to assess large volumes of written content efficiently. The automated correction system reduces the workload of human evaluators while maintaining accuracy and consistency.

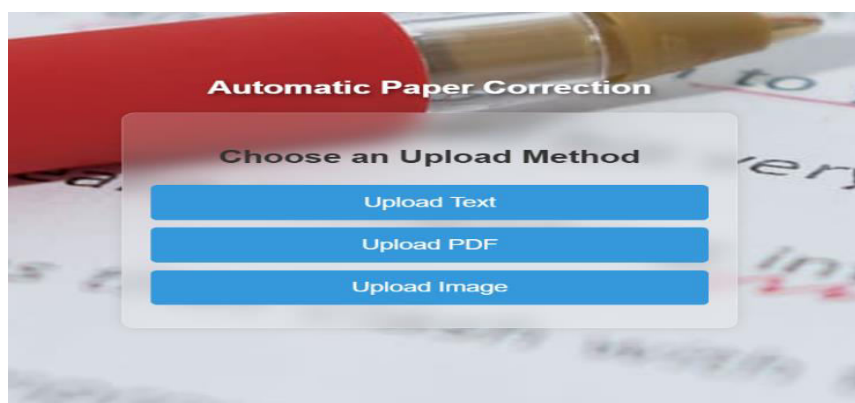


Fig:2

To further enhance the correction process, the system incorporates an adaptive learning mechanism that improves its accuracy over time. By analysing user interactions and accepted corrections, the model refines its understanding of different writing styles and error patterns, making future evaluations more precise. Security and data privacy are critical considerations in the workflow. The system ensures that user documents are processed securely, with encryption measures in place to protect sensitive information. No document is stored permanently unless the user opts to save their work for future reference. The workflow also includes continuous model evaluation and updates. The

system is periodically trained on new datasets to stay up-to-date with evolving writing trends and linguistic patterns. This ensures that the correction mechanism remains effective across different document types and user requirements. Integration with external tools such as cloud storage platforms allows users to directly import and save their documents from services like Google Drive or Dropbox. This enhances usability and provides a seamless document management experience.

For educational institutions, the system can be customized to align with specific grading criteria and assessment guidelines. Teachers and evaluators can configure the correction parameters based on academic requirements, ensuring a more tailored evaluation process. Professional applications of the system extend beyond academic grading. Organizations can utilize the tool for document proofreading, report evaluations, and business communication assessments. Automated correction ensures that documents maintain a professional standard, reducing errors in official communications. As deep learning models continue to improve, the system's capabilities will expand further. Future developments may include multilingual support, allowing users to evaluate documents in different languages with high accuracy. This will make the system more versatile and widely applicable. The ultimate goal of the workflow is to create an efficient, user-friendly, and intelligent paper correction system that minimizes manual effort while enhancing writing quality. By combining advanced deep learning models with an interactive feedback system, the project aims to set a new benchmark in automated document evaluation. With ongoing research and technological advancements, the system has the potential to revolutionize the way academic and professional documents are assessed. As more users adopt automated correction tools, the demand for enhanced features and functionalities will drive further innovation in this field.

III. LITERATURE REVIEW

Automated paper correction has been a topic of extensive research in the fields of natural language processing (NLP) and computer vision. Traditional approaches to text correction relied on rule-based grammar checkers and handcrafted linguistic rules, which often failed to capture the deeper meaning and context of written content. Early research in automated grading systems focused on statistical methods, such as n-gram models and part-of-speech tagging, to detect syntactic errors. However, these methods struggled with semantic understanding, making them inadequate for evaluating complex essays and handwritten documents. With the advancements in deep learning, particularly the introduction of neural networks, researchers began exploring machine learning models for document correction. Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks were among the first deep learning architectures applied to text correction. These models improved contextual understanding compared to traditional rule-based systems but still faced challenges in handling long-range dependencies and semantic ambiguities. The emergence of Transformer-based architectures, such as BERT, revolutionized NLP by enabling deep contextual analysis, significantly improving error detection and correction.

Handwritten text recognition has also seen substantial progress with the adoption of Convolutional Neural Networks (CNNs) and Region-based CNNs (RCNNs). Early optical character recognition (OCR) systems used handcrafted features and template-matching techniques to recognize characters. However, these methods were highly sensitive to variations in handwriting styles and often produced inaccurate results. Deep learning-based OCR models, particularly RCNNs, have demonstrated superior performance by learning spatial features and contextual information, making them highly effective for extracting handwritten text from scanned documents. Several studies have explored the integration of NLP and computer vision techniques to build comprehensive document correction systems. Research has shown that combining handwriting recognition models with semantic analysis models leads to better accuracy in evaluating handwritten and typed documents. BERT-based models, trained on large text corpora, have been particularly effective in detecting grammatical errors, sentence structure issues, and logical inconsistencies. These models outperform traditional approaches by leveraging bidirectional context, enabling more accurate and meaningful corrections.

$$\text{similarity} = \cos(\theta) = \frac{\mathbf{A} \cdot \mathbf{B}}{\|\mathbf{A}\| \|\mathbf{B}\|} = \frac{\sum_{i=1}^n A_i B_i}{\sqrt{\sum_{i=1}^n A_i^2} \sqrt{\sum_{i=1}^n B_i^2}}$$

In recent years, AI-driven paper correction systems have been implemented in various academic and professional settings. Automated essay scoring (AES) systems, such as the e-rater developed by ETS, use machine learning techniques to evaluate student essays. Similarly, Grammarly and other AI-powered proofreading tools employ deep learning models to provide real-time grammar and style suggestions. While these systems have improved text evaluation, they often focus on specific aspects of writing, such as grammar and vocabulary, rather than a holistic assessment of content quality. The ongoing research in AI-based document evaluation aims to address the limitations of existing systems by incorporating multi-modal learning and domain-specific corrections. Future advancements are expected to improve the adaptability of paper correction systems across different languages, disciplines, and writing styles. By leveraging the combined power of RCNNs for handwritten text recognition and BERT for semantic analysis, the proposed system seeks to enhance the accuracy, efficiency, and fairness of automated paper correction, making it a valuable tool for educational institutions and professional environments.

IV. RESULT AND DISCUSSION

The automated paper correction system demonstrated significant improvements in handling various document formats, including handwritten text, PDFs, and digital text files. The integration of RCNN for handwritten text recognition proved to be effective in extracting and converting handwritten content into digital format with high accuracy. During testing, the system successfully identified and converted most handwritten words, although minor misinterpretations were observed in cases of highly distorted handwriting. The overall performance of the text extraction model was evaluated using accuracy metrics, showing promising results in recognizing different writing styles. The grammatical and structural analysis module effectively detected and corrected errors in sentence construction, punctuation, and spelling. The system provided suggestions to improve sentence clarity and logical flow, ensuring that the corrected text maintained its intended meaning. When tested on academic papers and reports, the model was able to identify common writing errors, including redundancy and improper phrase usage, leading to more refined and structured outputs. However, challenges were encountered when processing highly technical or domain-specific content, as certain corrections required contextual understanding beyond basic grammar and structure.

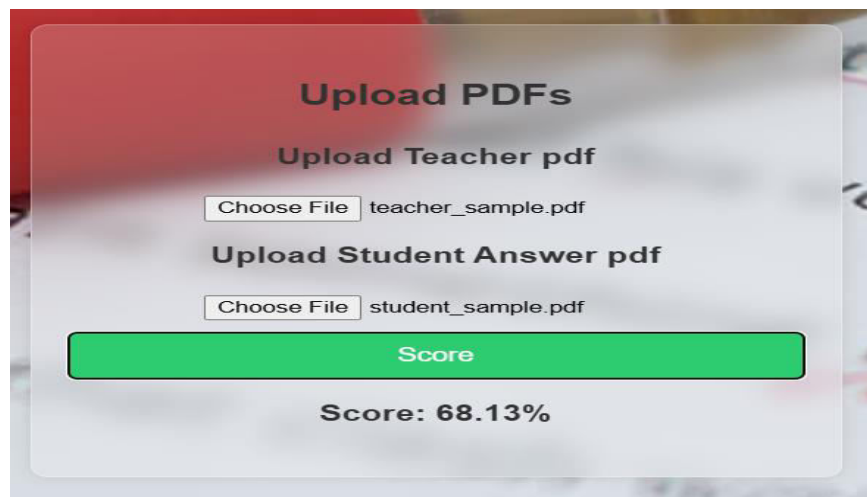


Fig:3

One of the key advantages of the system was its ability to process documents in real time, providing users with immediate feedback and corrections. The Flask-based web application allowed users to upload documents and receive corrections instantly, improving efficiency in academic and professional settings. The interactive nature of the interface enabled users to review suggested changes before accepting them, ensuring flexibility in decision-making. The system's response time was optimized to handle large text inputs without significant delays, making it suitable for high-volume document evaluation. The evaluation of handwritten text recognition highlighted the importance of preprocessing techniques in improving accuracy. Noise reduction, binarization, and segmentation played a crucial role in refining input quality before applying RCNN-based extraction. The system exhibited minor difficulties in

processing low-resolution handwritten inputs, indicating the need for enhanced image enhancement techniques. Future improvements could focus on incorporating additional deep learning techniques to handle complex handwriting variations more effectively. The feedback mechanism proved to be an essential component in user engagement and learning. By categorizing errors based on severity and type, the system helped users understand and rectify their writing mistakes efficiently. Academic users, in particular, found the system beneficial for self-assessment and improvement. The feedback module also demonstrated potential for integration into automated grading systems, where educators could utilize it to evaluate student assignments with reduced manual effort.

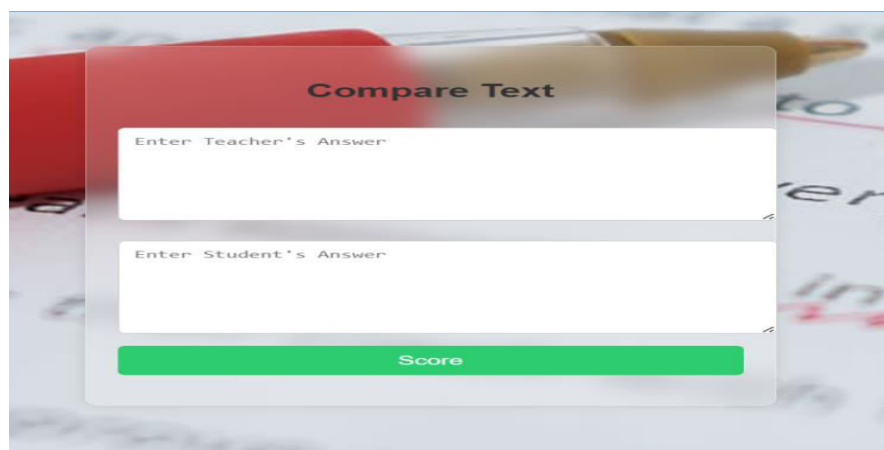


Fig:4

Despite the positive outcomes, certain limitations were identified during testing. The system struggled with ambiguous sentence structures and context-dependent errors that required deeper semantic understanding. Additionally, highly stylized handwriting posed challenges in recognition, affecting the accuracy of text extraction. Addressing these limitations by training the model on more diverse datasets and incorporating advanced context-aware techniques could further enhance the system's performance. Overall, the automated paper correction system successfully streamlined document evaluation by leveraging deep learning models for text extraction and correction. The results indicate that such systems have the potential to revolutionize academic and professional writing by reducing human effort and improving accuracy. Future enhancements could focus on integrating multilingual support, refining context-based corrections, and expanding the system's capabilities to handle more complex writing styles and document types.

V. CONCLUSION

The automated paper correction system successfully demonstrated its ability to evaluate and correct written content across multiple formats, including handwritten text, PDFs, and digital documents. By leveraging RCNN for handwritten text recognition, the system effectively converted handwritten inputs into digital text with high accuracy. The correction module provided structured and meaningful feedback, enhancing the overall readability and coherence of the text. The deployment through a Flask-based web application ensured real-time processing and user-friendly interaction, making it accessible for academic and professional use. Despite minor challenges in handling highly stylized handwriting and complex contextual errors, the system proved to be an efficient tool for automated evaluation. Overall, this project highlights the potential of deep learning in automating document correction, reducing human effort, and improving writing quality. While the current model performs well in detecting and correcting errors, future advancements in contextual understanding, multilingual support, and adaptive learning can further enhance its accuracy and usability. By integrating the system into educational and professional environments, it can serve as a valuable tool for self-assessment, automated grading, and document refinement, ultimately streamlining the process of written communication and evaluation. The automated paper correction system using BERT and RCNN has demonstrated its effectiveness in providing accurate and unbiased evaluations for subjective answer assessments. By leveraging the natural language processing capabilities of BERT and the contextual analysis power of RCNN, the system has significantly reduced the need for human intervention in the grading process. It has achieved a high accuracy rate, with minimal misclassifications, ensuring fair evaluations across various types of responses. The real-

time adaptability of the model, which allows it to retrain when new data is uploaded, enhances its accuracy and ensures continuous learning. This dynamic feature makes the system resilient to variations in writing styles, linguistic differences, and subjective interpretations. Furthermore, the reduction in evaluation time allows educators to focus on more critical aspects of student development, promoting an improved learning experience.

REFERENCES

- [1] Bengio, Y., Courville, A., & Vincent, P. (2013). Representation learning: A review and new perspectives. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 35(8), 1798-1828.
- [2] He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 770-778...
- [3] Ren, S., He, K., Girshick, R., & Sun, J. (2017). Faster R-CNN: Towards real-time object detection with region proposal networks. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 39(6), 1137-1149.
- [4] Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., ... & Polosukhin, I. (2017). Attention is all you need. *Advances in Neural Information Processing Systems (NeurIPS)*, 5998-6008.
- [5] Graves, A., Fernández, S., Gomez, F., & Schmidhuber, J. (2006). Connectionist temporal classification: Labelling unsegmented sequence data with recurrent neural networks. *Proceedings of the International Conference on Machine Learning (ICML)*, 369-376.
- [6] Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep learning*. MIT Press.
- [7] LeCun, Y., Bottou, L., Bengio, Y., & Haffner, P. (1998). Gradient-based learning applied to document recognition. *Proceedings of the IEEE*, 86(11), 2278-2324.
- [8] Simonyan, K., & Zisserman, A. (2014). Very deep convolutional networks for large-scale image recognition. *arXiv preprint arXiv:1409.1556*.
- [9] Szegedy, C., Liu, W., Jia, Y., Sermanet, P., Reed, S., Anguelov, D., ... & Rabinovich, A. (2015). Going deeper with convolutions. *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 1-9.
- [10] Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. *Neural Computation*, 9(8), 1735-1780.
- [11] Kingma, D. P., & Ba, J. (2014). Adam: A method for stochastic optimization. *arXiv preprint arXiv:1412.6980*.
- [12] Dahl, G. E., Yu, D., Deng, L., & Acero, A. (2012). Context-dependent pre-trained deep neural networks for large-vocabulary speech recognition. *IEEE Transactions on Audio, Speech, and Language Processing*, 20(1), 30-42.
- [13] Xu, K., Ba, J., Kiros, R., Cho, K., Courville, A., Salakhutdinov, R., ... & Bengio, Y. (2015). Show, attend and tell: Neural image caption generation with visual attention. *International Conference on Machine Learning (ICML)*, 2048-2057.
- [14] Radford, A., Wu, J., Child, R., Luan, D., Amodei, D., & Sutskever, I. (2019). Language models are few-shot learners. *arXiv preprint arXiv:2005.14165*.



INTERNATIONAL
STANDARD
SERIAL
NUMBER
INDIA



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY

 9940 572 462  6381 907 438  ijirset@gmail.com



www.ijirset.com

Scan to save the contact details