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Automating the grading of handwritten examinations through the integration of optical character recognition and machine learning algorithms

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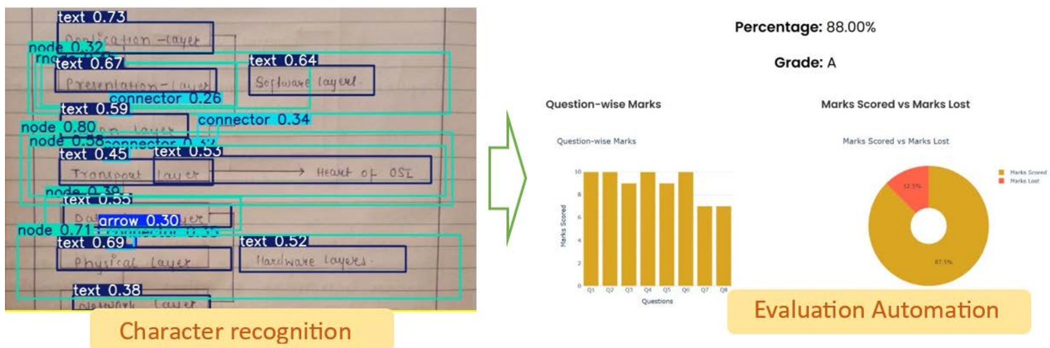
Article



ABSTRACT

High-end techniques from OCR and machine learning help design a very efficient and accurate grading system for written assignments and exams. A system that uses OCR to digitize the submission from the students makes it feasible to automatically check the assignments against predefined criteria so as not to allow human biases or errors to creep in to delay the grading process. Trained models include detection and scoring of block diagrams, mathematical expressions, and graphical representations; auto-recognition and grading of complex visual content is easily achievable by utilizing key innovations. The system provides adaptation to different handwriting, contextual understanding for scoring difficult responses, and instant feedback that tracks performance and customized grading norms with the instructors. All of these had transformed the grading process in terms of efficiency and objectivity while remaining very versatile in the education assessment process.

Keywords: Handwritten Text Recognition, OCR, PyTesseract, NLP, Automated Grading System, Machine Learning, Educational Assessment

INTRODUCTION

Grading assignments and tests manually has become very common in educational institutions. However, this has become the new trend, and in so doing, it surely presents a big problem for the teachers, who are necessarily required to grade the assignments both in time, in fairness, and in accuracy. Manual grading requires a lot of time and is exposed to human error and inconsistency. In such a scenario, application of technology to automate tasks has become truly crucial to improve the grading process. The usage of Optical Character Recognition (OCR) and Machine Learning (ML) can make the examination of handwritten response sheets machine-based, thereby possibly transforming the process of educational assessment into an efficient system devoid of inaccuracies.

Text that has been printed or written can now be converted to machine-readable form with OCR technology. However, the complexity and diversity of handwriting have proven difficult for conventional OCR algorithms to handle. With the recent advancement in OCR and super potent ML models, now it is possible to reliably detect and analyze several handwriting styles such as text, diagrams, and mathematical expressions. Answer sheets can be seamlessly digitized as part of the multiple technologies used in an automated grading system, which can handle thousands of student submissions with minimal human assistance.

Machine learning algorithms are thus an integral part in the interpretation of the content of the digital response sheets. This means that models are taught to identify the structure and semantics of the answers, which would later help them grade responses that conform with pre-defined grading rubrics. Such a process includes catching important ideas, pertinent details, and recognizing intricate patterns in answers. The system can learn from data and adjust to the various student writing styles and subject-specific subtleties, thus slowly increasing its accuracy. Additionally, the ML component ensures that grading is fair, unbiased, and consistent in a manner free of the biases that may affect human graders.

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Besides saving time, an OCR and ML-powered automatic grading system presents a myriad of other benefits. It gives teachers immediate feedback on the performance of students, enabling them to concentrate on more advanced duties like curriculum design and interactions with the students. Moreover, the system provides insightful information on the learning habits of students, enabling teachers to recognize regions that require extra help. By combining the potential of OCR and ML, the method disrupts the conventional process of grading in a much more reliable, scalable, and effective manner for educators and students.

LITERATURE SURVEY

Optical Character Recognition (OCR) is an extensively researched subject in image understanding and pattern classification. Conventional techniques tend not to perform correctly in character recognition of scanned written documents. Traditional work has presented a range of machine learning paradigms towards enhancing character detection. Convolutional Neural Networks (CNNs) have arisen as a high-potential solution because CNNs can detect features automatically as well as classify images. Interestingly, CNN-based research has proved outstanding recognition accuracy for highly complex handwritten patterns [1]. The use of CNNs on automatic grading systems has proved remarkably advantageous, especially in educational institutions.

The majority of available systems are centered on objective-type, single-line responses, with narrow success in grading complex descriptive answers. Machine learning algorithms, particularly Artificial Neural Networks (ANN) with backpropagation, have been used extensively in research to enhance accuracy in automatic grading systems. These methods generally use keyword matching and answer length verification. Two major challenges continue to exist, though: handwriting diversity and content diversity. Recent developments in the integration of OCR for handwritten text assessment have resulted in enhanced accuracy, with an automated grading system scoring 92.86% testing accuracy [2].

Recent work in computer short-answer scoring is increasingly using Natural Language Processing (NLP) techniques for speedier and more accurate assessment. Handwritten answers create difficulties for classical scoring techniques, and hybrid solutions are required to combine handwriting recognition with NLP. Agreement tests, in terms of Cohen's kappa coefficient, show that the performance of automatic systems can match human agreement levels in scoring, from 0.86 to 0.95 [3]. The evidence is strong enough to suggest the feasibility of completely automating short-answer scoring (SAS) systems in education.

Most of the research studies have addressed the problems in handwriting recognition with the diversity in writing style and interpretational variance. Digitization across the world has significantly enhanced reading and access because a printout of any given information in digital format is readily available. These new developments [4] in machine learning, especially the application of CNN, have brought phenomenal success in almost all applications of pattern recognition, from the beginning to the classification of handwritten digits. For example, using MNIST datasets with OpenCV tools, researchers were able to gain human levels of accuracy in the real-time recognition of digits while highlighting the potentiality of deep learning techniques.

D. Hijam et.al. [5] extends the work done so far in handwritten character recognition, where most of the conventional classifiers like KNN, SVM, and Random Forest are implemented along with handcrafted feature descriptors. Most of the research has been concentrated on the most commonly studied scripts, while the vast data sets for the less-studied scripts like Meitei Mayek remain uncovered. The recent significant breakthroughs in CNNs also seem to carry good performance relative to the traditional methodologies, as it learn features right from the data provided for images. This work adds to that purpose with the presentation of a large scale Meitei Mayek handwritten character database as well as the assessment of recognition using both standard classifiers and an optimized CNN model.

G. Sanuvala et.al.[6] eliminates the issues plaguing the process for grading from a traditional process of written examination evaluation that is laborious, and notorious for some inconsistency with judgmental parameters-the ignorance of the assessor about the subject of study or less time available for evaluation. The research outlines inefficiencies in the manual grading process and opens a shut automated solution in the form of the Handwritten Answer Evaluation System. Novelty This paper is novel in approaching the checking of unscored descriptive answers through Optical Character Recognition technology, text extraction, and machine learning methods based on cosine measures to grade results. Results Based on the outcomes, the proposed HAES can significantly improve efficiency and reliability in assessing written examinations, coupled with a large contribution to the integration of educational technology.

However, human judgment is still very much relied upon in current assessment practice, particularly in the case of descriptive answers which are supposed to go offline. Some of the papers in the section immediately preceding have already hinted at problems with such a process. The problems pose a need for an efficient and reliable system of automated assessment. Probably, one of the most relevant fields in Machine Learning for this purpose is Handwritten Text Recognition, where considerable activity has been sensed and where several models have been proposed both for online as well as offline applications. The survey by K. Devan et.al. [7] synthesized different methodologies of evaluating objective as well as descriptive answer sheets in an automated manner. It, therefore, tries to capture the state of the art in offline HTR and indicate gaps that might be pursued further in future research. Handwriting character recognition forms part of the necessity of digitizing the handwritten input from multiple sources; however, it comes with different individual styles making it a problem for reading the perception.

K. Gothur et.al. [8] reported a web-based application where it employs neural networks to compute the mathematical equations sketched by students from their notebooks and addresses the issue of manual gradings in the academic setting. In this provided scenario, the application calculates an arithmetic or linear equation with the assistance of the camera-based input mechanism. Thus, it is coupled with an extensive use of sophisticated machine learning methods for automation in the evaluation process and making precision flawless.

An operation scanning photocopied question papers and estimating marks for an examination is very time-consuming and thus leads to work into automated methods using image processing techniques. R. Deepa et.al.[9] applied Optical Character `Recognition to scan charts for analysis using various preprocessing techniques, including edge detection filters such as Sobel, Canny, and log-Gabor, and discriminant analysis to establish a suitable threshold for evaluation. This assignment ensures that the Support Vector Machine trained on the MNIST dataset classifies to identify an accurate identification of the handwritten digit. Such a method ensures that results obtained depict the SVM algorithm simply flattening the score in the evaluation charts.

Recent Trends on Automatic Location and Recognition in Educational Environment with Properly Considering Datasets Synthesising for Hand-written Text Locating Inside Scanned Answer Sheets. K. Wu. et.al.[10] method generated an executable synthetic dataset consisting of 5,000 images with over 2,500 annotations enabling training of a CTPN text-line detection network from scratch. The optimized handwritten text-line recognizer, i.e., MLC-CRNN with CRNN architecture, was highly successful in overcoming handwriting recognition challenges that are actually distinct from scene text features and significantly enhanced recognition accuracy. The solution now provides a valuable tool for large-scale assessments of English compositions.

COVID-19 brought this shift that changed and transformed how evaluation processes are undertaken to the extent that many sheets of written responses have to be hand-graded making such a process increasingly cumbersome. It assumes the implementation of a system with smartphone scanners to scan such sheets in PDF and harnesses OCR technology in computation upon scoring. As such, system proposed by K.S. Koushik et.al. [11] delivered 89% ICR accuracy, 86% CNN accuracy, and 84% IWR accuracy; it is indeed efficient therefore excellent efficiency that enhances grading effectiveness and reliability.

The increasing need for an effective examination marking process has driven research into Intelligent Character Recognition technologies as part of optical character recognition of written alphanumeric characters. Having mentioned above the preceding sections were on the inadequacy of traditional hand-marking and the presence of a component that needed automated solutions for it to be efficient and accurate. Velasco, J.S. et.al.[12] combined certain machine learning techniques in developing a checker for test papers using OpenCV and Support Vector Machine algorithms. Experimentally verified on real examination data from 131 participants, the work achieved an accuracy level of 93.08%.

In the OCR area, it is added through the system of self-reading identifications and sorting of answer fields for information sheets in students' works. The proposed algorithm by A. Kocem et.al.[13] eliminates the challenge of distinguishing between the script language of Arabic and the script language of French since it integrates a decision tree-based approach, which helps enhance the field's classification and script identification. It even provided yields up to 92.5% in numeric fields, 94.34% in Arabic scripts, and 94.66% in French scripts. Large-scale experimental testing on 80 sheets has been found to establish that this does make it feasible to transform the printed data into a computerized form, which makes a good set of data achievable even for the databases. Block diagrams have gained to be very commonly used these days to model workflows pretty complex, though deciphering block diagrams would be the toughest mental workout.

Bhushan, S. et.al.[14] designed a new framework, called "BloSum, " for the translation of images of block diagrams into a textual summary by extraction of contextual triplets. In this paper, we curate a new dataset of complex computerized block diagrams and detail the preparation and analysis of this dataset. In our evaluation, the results show that BloSum outperforms the existing approaches by far, gaining much higher scores than them for automatic summarization of visual content.

One of the biggest problems not made easy with digitization is that of segmenting printed text; this is even truer since whole word recognition also comes with complexity. Agrawal, R. et.al.[15] brought new techniques wherein words are broken down into characters using a method involving bacteria foraging optimization that crafts artificial words. The approach proposed differs the valid characters from the rest just like the written words using a pixel model, which has an arrangement of bacterial colonies on both the parent and the offspring bacterial colonies. This will result in candidate segments by the offspring bacterial colonies; unhealthy variants are pruned to have an optimum character segmentation. The results of better accuracy in paragraph segmentation with more than 50 subjects mean testifying the effective working of this new algorithm by advancing digitization in text written by hand.

There has been significant development in the scheme of things, but the calculation and administration of examination marks are still extremely cumbersome and susceptible to human errors through errors committed. The system by L. Logeshvar et.al.[16] added the detection of marks from handwritten answer scripts using edge and contour detection methods adopted from image processing as well as Convolutional Neural Networks. It also suggests the automation of table recognition and calculation of the score aimed at enhancing the accuracy and effectiveness of the test with negligible interference from human agents.

METHODOLOGY

This work aims to design an automated grading system. A whole study has been made on giving and generating responses, grammar, spelling, context, and visual block diagrams.[17,18] This section elaborates in detail the design and development of the proposed system. Figure 1, Figure 2, and Figure 3 depict the architecture of the proposed system.

System Overview and Initial Processing

The proposed system begins its work with the preprocessing of the input PDF documents containing questions and answers. Such documents are made digital in arrays to further analyze them, which can be done uninterruptedly without any hitches.

Question and Answer Extraction:

PDF questions and the answer sheet PDF, where answers are tabulated on one page, are scanned, and they are translated into arrays in digital form. This creates a preliminary structure for questions to function as keys and their corresponding answers to act as values. The mapping also ensures proper alignment of questions and answers for proper evaluation.

Section-wise Mapping:

These digitized arrays are arranged section-wise to maintain a structured evaluation process. These structured representations will help align the responses with their respective question categories, thus directing them for focused analysis.

Answer Generation and Validation:

The system will use a dual-path validation mechanism for cases when model answers exist, as well as cases when they do not. This allows for adaptability towards many scenarios of evaluation.

Model Answers Available:

If model answers are available, then these are scanned and section-wise mapped for a comparative study. This structured approach ensures that the student's response is properly compared with a reliable benchmark for every student.

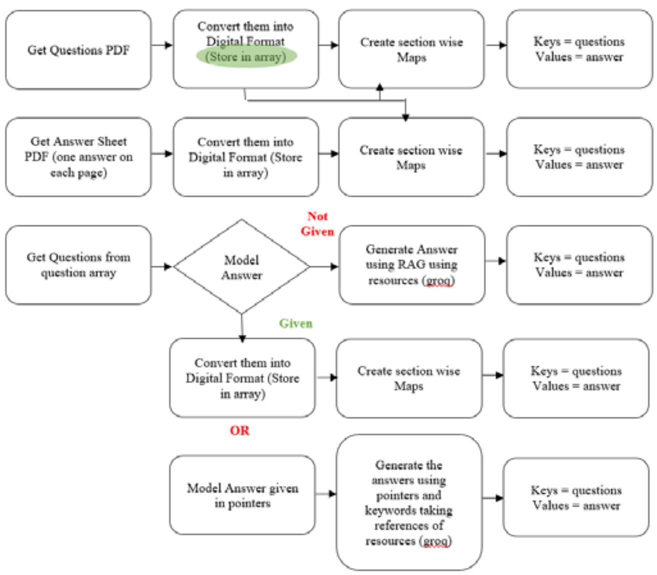


Figure 1: System Architecture Illustrating the Automated Evaluation Process of Handwritten Exams Using OCR and Machine Learning Techniques

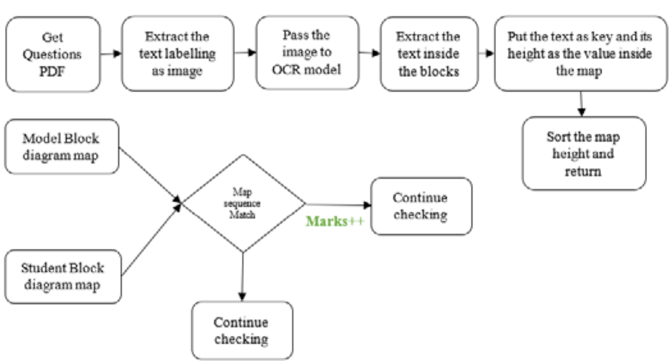


Figure 2: Block Diagram Representing the Algorithmic Process for Assessing Handwritten Examination Diagrams through OCR and Machine Learning Integration

Model Answers Not Available:

In the absence of model answers, the system uses Retrieval-Augmented Generation (RAG) techniques. It generates appropriate and contextually correct answers with the help of external resources and relevant databases. These generated answers are similarly structured and mapped for comparative evaluation.

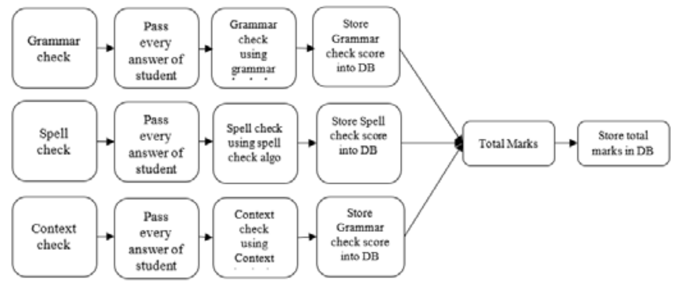


Figure 3: Text Evaluation for An Innovative Framework for Automating the Grading of Handwritten Examinations Through the Integration of Optical Character Recognition and Machine Learning Algorithms

MATHEMATICAL MODEL

Cohen's kappa

$$k_c = \frac{\sum_{j=1}^{n} u_{ij}(ii') - \sum_{j=1}^{n} p_{ij}p_{i'j}}{1 - \sum_{j=1}^{n} p_{ij}p_{i'j}}$$

This is a general mathematical model that measures agreement between two raters or classifiers across multiple categories. It accounts for observed agreement and chance-corrected agreement to better assess reliability. Normalizing the agreement score accounts for chance effects and is ideal for consistency assessments in multi-class classification problems, probabilistic assessments, and inter-rater reliability studies.

RESULTS AND DISCUSSIONS

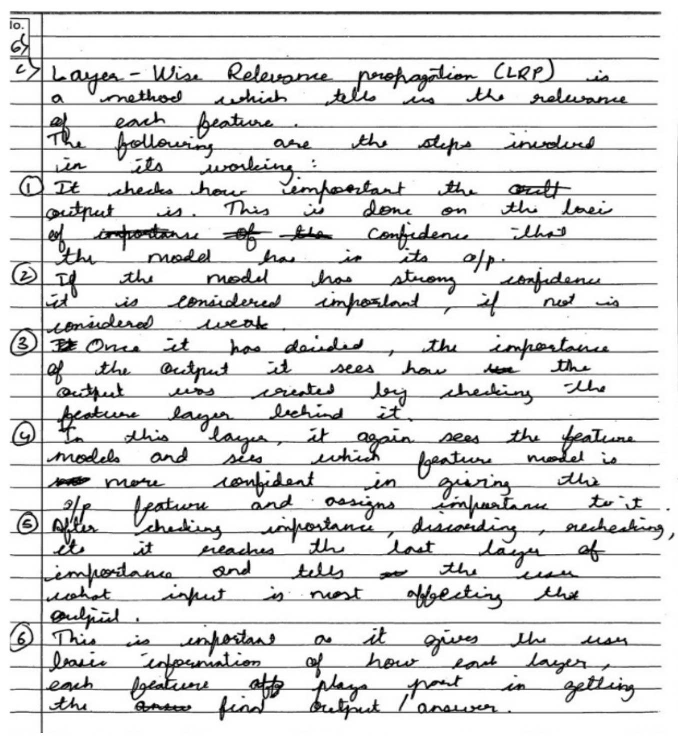
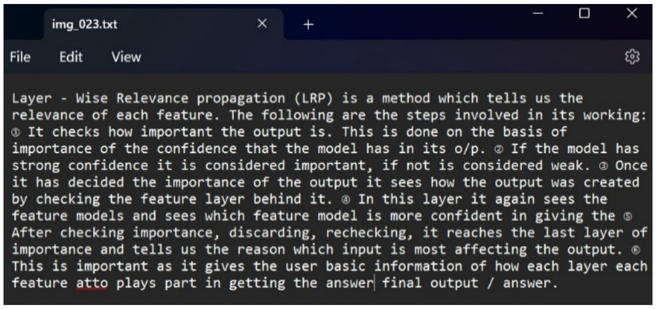

6) c) Layer-Wise Relevance propagation (LRP) is a method which tells us the relevance of each feature.
The following are the steps involved in its working:
① It checks how important the ~~outt~~ output is. This is done on the basis of ~~importance of the~~ confidence that the model has in its o/p.
② If the model has strong confidence it is considered important, if not is considered weak.
③ ~~It~~ Once it has decided, the importance of the output it sees how ~~we~~ the output was created by checking the feature layer behind it.
④ In this layer, it again sees the feature models and sees which feature model is ~~more~~ more confident in giving the o/p feature and assigns importance to it.
⑤ After checking importance, discarding, rechecking, etc it reaches the last layer of importance and tells ~~so~~ the user what input is most affecting the output.
⑥ This is important as it gives the user basic information of how each layer, each feature ~~ofp~~ plays part in getting the ~~answ~~ final output / answer.

Figure 4: Student Handwritten Answer


img_023.txt
File Edit View

Layer - Wise Relevance propagation (LRP) is a method which tells us the relevance of each feature. The following are the steps involved in its working: ① It checks how important the output is. This is done on the basis of importance of the confidence that the model has in its o/p. ② If the model has strong confidence it is considered important, if not is considered weak. ③ Once it has decided the importance of the output it sees how the output was created by checking the feature layer behind it. ④ In this layer it again sees the feature models and sees which feature model is more confident in giving the ⑤ After checking importance, discarding, rechecking, it reaches the last layer of importance and tells us the reason which input is most affecting the output. ⑥ This is important as it gives the user basic information of how each layer each feature atto plays part in getting the answer final output / answer.

Figure 5: OCR conversion of Student Handwritten Answer

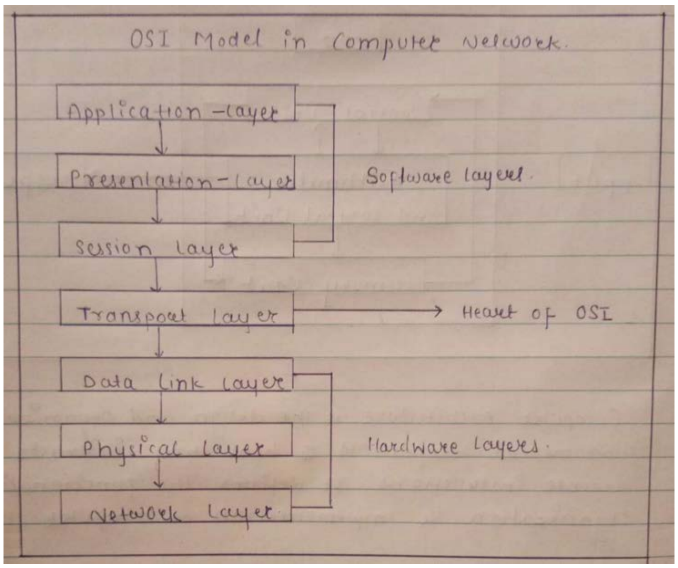


Figure 6: Block Diagram given for evaluation

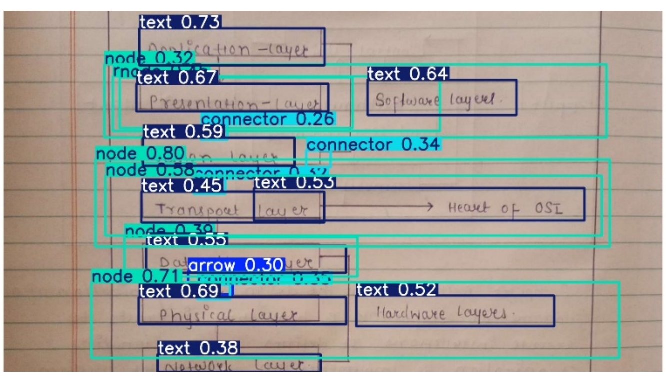
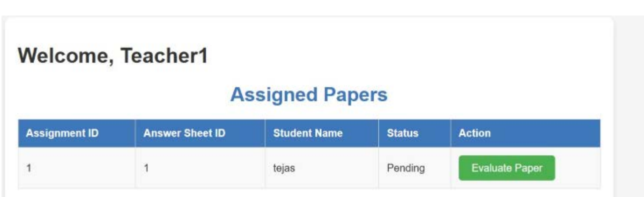


Figure 7: Evaluated Block Diagram


Welcome, Teacher1

Assigned Papers

Assignment ID	Answer Sheet ID	Student Name	Status	Action
1	1	tejas	Pending	Evaluate Paper

Figure 8: User Interface of the Proposed System for Automated Assessment of Handwritten Assignments and Exams using OCR and Machine Learning

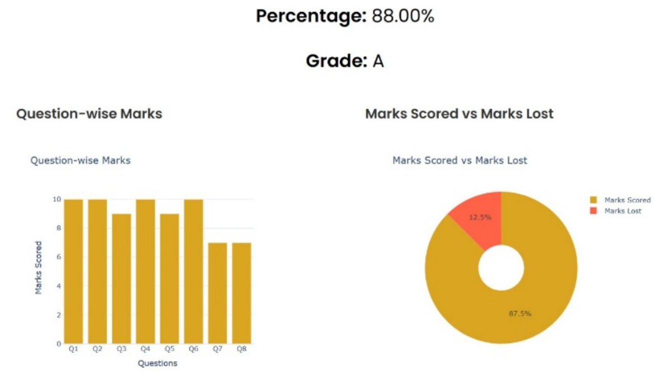


Figure 9: Generated Student Report for Automating the Grading of Handwritten Examinations Through the Integration of Optical Character Recognition and Machine Learning Algorithms

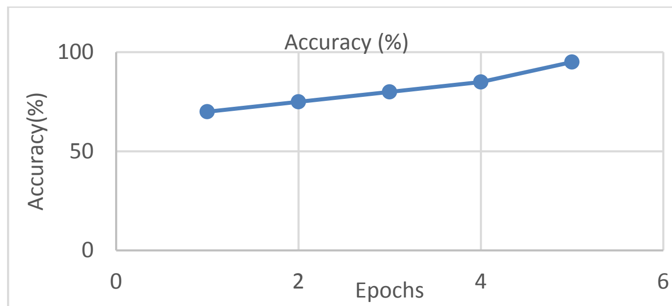


Figure 10: Improvement in Model Accuracy Across Training Epochs

Table 1. Comparison Between Manual Checking and Proposed System

Answer Script	Marks are allocated by manually checking	Marks allocated by System
1	10	10
2	9	9
3	9	9
4	10	10
5	10	9
6	9	8
7	8	8
8	9	9

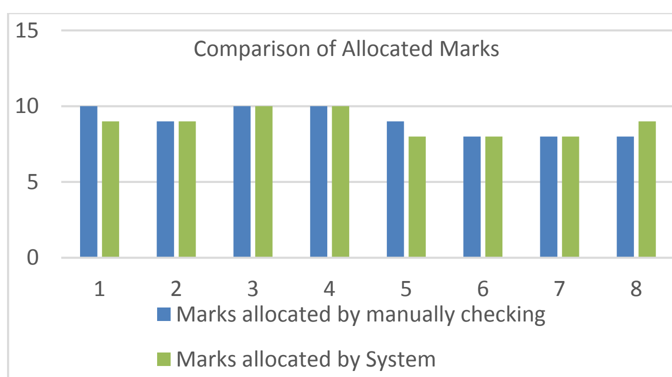


Figure 11: Graphical Representation Comparison Between Manual Checking and Proposed System

Table 2: Recognition Rate of Handwritten Words

Answer Script	Number of Words	Recognized Words	Recognition Rate
1	126	126	100%
2	77	76	100%
3	76	75	98.6%
4	148	147	99.3%
5	103	101	98.0%
6	103	102	99.0%
7	50	49	98.0%
8	43	43	100%

Table 3: Performance Metrics of the Proposed Model

Parameter	Value (%)
Answer Mapping Accuracy	95
Block Diagram Matching Accuracy	92
Grammar and Context Check	85

Table 4: Comparative Analysis of the Proposed System's Performance Versus Existing Evaluation Methods

Sr. no.	Model and Method Description	Accuracy
1.	A neural network model employing Support Vector Machines for offline handwritten character recognition [19]	62.93%
2.	A neural network-based system without explicit feature extraction instead using a hybrid feature extraction approach for handwritten character recognition [20]	91.88%
3.	A fuzzy logic-driven handwritten character recognition method utilizing global geometric feature extraction [21]	77.89%
4.	An assignment correction-focused recognition system leveraging row-wise segmentation for handwritten character input [22]	80%
5.	A Hidden Markov Model-based framework combining global and local feature extraction techniques for writer-independent handwritten English character recognition [23]	76.44%
6.	A CNN architecture based on LeNet-5 for offline English handwritten character recognition [24]	Upper 93.7% Lower 90.2%

The system proposed shows high accuracy in assessing handwritten answer scripts, as indicated by the performance measures and comparative studies presented. Figures 4 and 5 show the OCR module, which effectively converts handwritten text into digital form with minimal loss of accuracy, indicating the capability of the system to handle different handwriting styles. Figures 6 and 7 present the block diagram evaluation component, a critical feature that fills the gap in automated assessment by evaluating non-textual answers.

The user interface, as shown in Figure 8, promotes ease of integration into academic workflows through facilitating educators in uploading scripts, viewing results, and implementing required adjustments. Figure 9 equally supports the effectiveness of the system through generating a student report showing an overall breakdown of scores, identifying areas of strength and room for improvement.

One of the notable observations from Table 1 is the high level of consistency between the manual marks and the results of the suggested system. The slight variations, as observed in answer scripts 5 and 6, can be explained by illegible handwriting, indicating a need for the model to be further improved. Table 2 indicates the system's higher recognition rate, which is always over 98%, confirming its scalability and reliability for large-scale exams.

The accuracy statistics, which are compiled in Table 3, indicate the strength of the system in answering map (95% accuracy), block diagram assessment (92% accuracy), and grammar/context checking (85% accuracy). In comparison with current solutions (Table 4), the designed model performs better than conventional methods like Support Vector Machines (62.93% accuracy) and row-wise segmentation techniques (80% accuracy). It also compares competitively with hybrid neural networks and CNN-based approaches, with an upper-bound accuracy of 93.7%, thus emerging as a viable substitute in the arena of automated grading.

Comparison with Similar Studies:

Previous work in handwritten character recognition and grading systems has mainly revolved around enhancing the accuracy of OCR-based text conversion. The research based on hybrid feature extraction and local/global geometry techniques has reported accuracies from 76.44% to 91.88%. The suggested system incorporates both textual and non-textual assessment, setting it apart from previous work since it offers an end-to-end grading framework instead of an independent recognition module.

Furthermore, the majority of available grading systems lack contextual grammar checks and block diagram evaluations, which are essential for grading engineering and science-oriented answer scripts. Through the addition of these features, the suggested system closes the gap between rudimentary text recognition and all-around assessment methods.

Conclusion

The system proposed is effective in directly overcoming the issues of manual grading by taking advantage of more advanced OCR and machine learning techniques to grade handwritten answer sheets. It achieves high accuracy in the recognition of diverse handwriting styles and adds features that fill essential voids in existing automated grading systems, such as block diagram detection. Its effortless adoption and friendly characteristics ensure easy efficiency and consistency for educators during evaluation. Comparison with manual grading is done to indicate the reliability of the system, where minor discrepancies have further refinement areas. The system, in general, shows potential toward revolutionizing assessments in education, offering scalable, accurate, and efficient use in place of traditional methods, creating further potential for broader implementation in academic environments.

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CONFLICT OF INTEREST STATEMENT

Authors declare that there is no known financial or academic conflict of interest that might have influenced this work.

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