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eGrading, Automatic grading of student answer sheets using Computer Vision and Optical Character Recognition

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Abstract – *Technology playing key role in every profession in automating & improving productivity. When it comes to teaching profession, manually grading of student answer sheets is one of the most time-consuming activities. This research paper focuses on eGrading that automates grading of student answer sheets to reduce workload on teachers by using modern technology. Traditional character recognition techniques like Magnetic Ink Character Reader (MICR), Optical Mark Recognition (OMR), Optical Character Recognition (OCR) offer limitations in use and accuracy, with OCR being relatively efficient and flexible to use. With the advancements of Cloud computing and Software-as-a-Service (SaaS), online testing gained momentum where both questions and answers were stored in database and validated against student input answers for grading. Artificial Intelligence technologies like Computer Vision with Optical Character Recognition (OCR) can be used to grade student hand written answer sheets that would significantly mitigate the limitations. A python-based prototype solution framework using computer vision and OCR methods trained by machine learning is discussed.*

Key Words: Grading, Answer Sheets, Artificial Intelligence, Computer Vision, Optical Character Recognition, OCR, Software-as-a-Service, OMR, MICR

1. INTRODUCTION

COVID made its impact felt across the globe, across industries & professions. 'Teaching' profession is no exception. During COVID, Teacher's burden significantly increased to balance between managing health and continue to provide learning experience to students. Many schools/teachers were forced to quickly adapt to digital technologies to sustain during / post-COVID era. This resulted in stress/fatigue in teachers and started quitting their job. As a result, teacher shortage has been marked as a major community problem. School & Colleges have been struggling to find and hire qualified teachers, and the pandemic has only intensified the situation. Millennials and Generation Z are less interested in pursuing teaching as a career. A greater population indicates a greater demand for teachers. All factors together intensified the problem and need to accelerate ways to mitigate community impact gained importance.

1.1. eGrading – automated grading to reduce burden on teachers.

The 1st Annual teachers survey done by Merrimack college indicated that the percentage of teachers who felt satisfied dropped from 62% in 2008 to 12% in 2022. 44% of teachers feel somewhat disappointed and are likely to leave in 2 years.

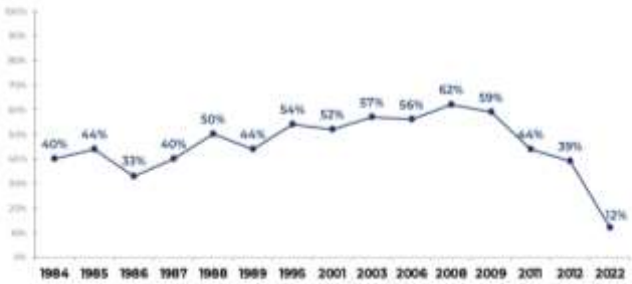

Fig -1: Percentage of K-12 teachers who say they are 'very satisfied' in their jobs. Source: Merrimack & MetLife Survey of American Teachers.

Merrimack college teacher survey also finds three main areas where teachers spend more time – teaching, grading, planning. While teaching is considered as core value add of teaching profession, time spent on grading answer sheets is a non-value add activity. While grading can be provide feedback to teachers and students on where to focus on improvements, same can achieved through automation of grading answer sheets (eGrading). Focus of this research article is explore various methods of eGrading.

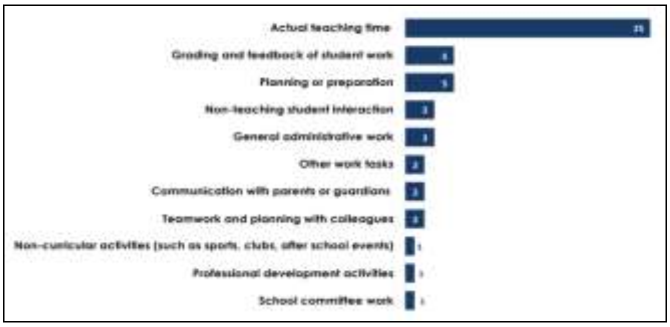

Fig -2: Time spent by teachers per week. Source: Merrimack Survey of American Teachers.

2. Research existing solutions

Students typically submits answer sheets either as paper based (hand written) or filled on line. Grading of online submissions can be much easier as answers can be digitally compared with pre-defined answers. When it comes to paper-based submissions, hand written answers need to be converted into digital characters before comparing with pre-defined answers. As hand written answer sheets offers flexibility / ease of use for school administration/teachers /students, focus of this research is to improve the accuracy of character recognition/grading. Traditionally there are three techniques were used for character recognition.

2.1 Magnetic Ink Character Reader

Magnetic Ink Character Reader (MICR) uses magnetic ink and special characters for recognizing characters. This is primarily used in banks for reading account numbers, this is not widely used for eGrading of student answer sheets due to its limitation in reading special fonts/characters only. MICR uses two different fonts (1) E-13B fonts - widely used by US, UK, Australia, Canada & Asian countries (2) CMC-7 font – used mainly in Europe and South America.

As it names stands, MICR methods involves magnetizable ink (typically Iron Oxide) that is used to print on a line using one of the MICR font. When it is sent through a scanner the fonts are magnetized and scanner detects the actual characters.

2.2 Optical Mark Recognition

Optical Mark Recognition (OMR) allows a pre-defined template for students to circle the answer choices with pencil. This answered template is scanned through a special optical scanner using beam of light to detect circles that are filled vs non-filled, ultimately grading the answer sheets. This method is mainly used in competitive exams, not widely used in day-to-day grading.

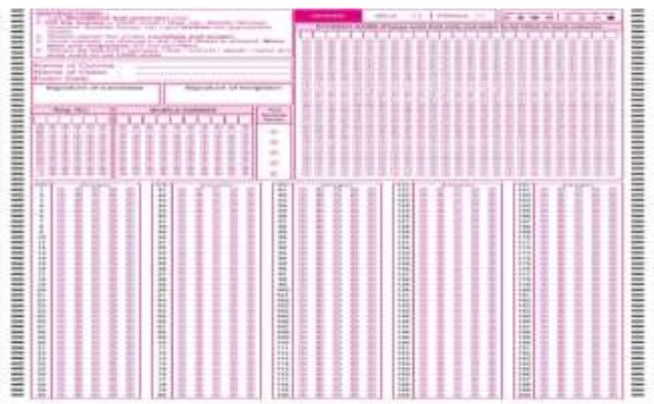

Fig -3: OMR Sheet example.
Source: https://www.omrsheet.com/omr-sheet-samples.php

2.3 Optical Character Recognition

OCR stands for Optical Character Recognition, modern technology used to convert image, printed or handwritten text into machine-readable text or digital content. It's a 5-step process that involves scanning or capturing an image of text and then using software to recognize and extract the characters and words from that image. OCR technology is commonly used to digitize printed documents, making them searchable and editable on a computer.

Image Capture: The step begins with capturing an image of the text you want to convert. This can be done using a scanner, a digital camera, or even a smartphone camera. The quality of the image is crucial for accurate OCR results, as factors like resolution, lighting, and alignment can affect the recognition process.

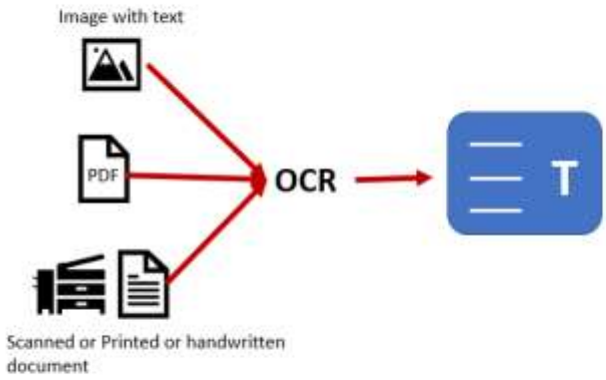

Fig -4: Document formats converted by OCR
Source: https://towardsdatascience.com/an-introduction-to-optical-character-recognition-for-beginners-14268c99d60

Preprocessing: The captured image may undergo preprocessing to enhance its quality. This can involve tasks like image straightening, noise reduction, and contrast adjustment to make the text more legible. Among all the steps, pre-processing is the most important as it has huge impact on accuracy and content quality. Pre-processing involves several sub-process steps.

Table -1: OCR pre-processing steps

De-Skewing	Removes any skewness in the scanned document
De-Speckling	Smoothens the edges, removes positive/negative spots
Layout analysis	Analyzes the images, paragraphs, lines, words
Binarization	Converts color images to black and white or grey scale version

Line & word detection	Find the spaces that separates the words, lines.
Line removal	Removes any borders, lines
Scaling	Adjusts the aspect ratio and scales the image to uniform size

Text Detection: OCR software then locates the text within the image. It identifies the boundaries of paragraphs, sentences, and individual characters. This step is crucial for accurately recognizing and preserving the layout and formatting of the original document.

Character Recognition: The core of OCR is character recognition, where the software analyzes each character within the identified text regions. It compares the shapes and patterns of the characters in the image to a database of known characters (fonts) and tries to match them.

Text Output: Once characters are recognized, OCR software reconstructs them into words, sentences, and paragraphs. The output is typically provided as plain text, which can be edited and searched on a computer. In some cases, OCR software may also provide formatting information to preserve the original layout.

While OCR technology has advanced significantly, it may still have limitations, especially when dealing with handwritten text, low-quality scans, or complex layouts. Accuracy can vary depending on the quality of the input image and the capabilities of the OCR software being used.

3. eGrading – Modern approaches using Artificial Intelligence and Computer Vision

With the advancements in cloud computing, artificial intelligence and machine learning technologies, some of the limitations of traditional OCR techniques can be overcome. Modern OCR solutions embrace machine learning and computer vision to recognize characters more accurately. Beyond text, computer vision can supports interpreting the image, colors, objects.

Subscription based/premium solutions: Amazon Textract, Microsoft's cognitive service, Google's cloud vision are proven solutions that can do the job. They offer Application Programming Interface (API) for easily calling the API by inputting the scanned paper and get content in the output/results.

Open source based solutions: There are several open source bases OCR services available that are equally good and does the job most of the time. Pytesseract, EasyOCR, Keras-OCR are few popular ones. All three solutions are available as python packages for ease of installing and using with Python. EasyOCR is the lightest weight solution and works for basic text extract from a pdf or image.

Computer vision plays a crucial role in Optical Character Recognition (OCR) by providing the technology and techniques needed to extract text from images or video frames. Here's how computer vision can be used in OCR:

Text Detection: Computer vision algorithms can be used to locate and identify text regions within an image or video frame. This involves identifying areas of the image where text is present and drawing bounding boxes around those regions. Various techniques, such as edge detection, contour analysis, and deep learning-based methods like Faster R-CNN or YOLO (You Only Look Once), are employed for text detection.

Text Localization: Once text regions are detected, computer vision techniques can be used to precisely localize individual characters or words within those regions. This involves segmenting the text into smaller units for recognition. Methods like Connected Component Analysis (CCA) and contour-based segmentation can be used for this purpose.

Character Recognition: Computer vision is used for character recognition within the localized text regions. Deep learning models, such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), are commonly employed for character recognition. These models are trained on a dataset of labeled characters to recognize the shapes and patterns of individual characters within the text.

Preprocessing: Computer vision can enhance the quality of the input image or video frame through preprocessing techniques. This may involve tasks like noise reduction, image rotation, contrast adjustment, and perspective correction. Preprocessing helps improve the accuracy of character recognition.

Layout Analysis: OCR often needs to preserve the layout and formatting of the original document. Computer vision can be used for layout analysis to identify elements like paragraphs, headers, and lists. This information is essential for maintaining the structure of the recognized text.

Post-processing: After character recognition, computer vision techniques can be employed for post-processing to correct errors, such as fixing misrecognized characters or formatting issues. Post-processing may also involve spell-checking and grammar checking to improve the quality of the recognized text.

Real-time OCR: In applications where OCR needs to be performed in real-time, computer vision is used to continuously analyze video frames, detect text regions, and perform character recognition. This is common in applications like license plate recognition, text recognition in video streams, and augmented reality.

Handwriting Recognition: Computer vision can be used to recognize handwritten text, which is often more challenging than printed text recognition. Handwriting recognition systems utilize deep learning models trained on datasets of handwritten characters and words.

Multilingual OCR: Computer vision-based OCR can support multiple languages by training recognition models for various scripts and languages. This enables the recognition of text in different languages and scripts within the same document.

Computer vision technologies have significantly improved the accuracy and efficiency of OCR systems, making them capable of handling a wide range of applications, from digitizing printed documents to extracting text from images and videos in real-time. These technologies continue to evolve, making OCR even more versatile and accurate across various use cases.

3.1 Prototype Solution

Solution Overview: A website using python flask web framework is built with all the pre-requisite python package. This website allows the teachers to pre-define answers against each test id. Students use the website to upload the scanned answer sheet or use mobile camera to directly take a picture and upload image of answer sheet.

Table -2: Software packages used in this solution

Python	Programming language with packages & virtual environment
EasyOCR	For Character recognition
OpenCV	Computer Vision library for image reading & modification
Flask	Web framework to build application, alternate web frameworks can also be used

Sample webpage demonstrating answer sheet upload.

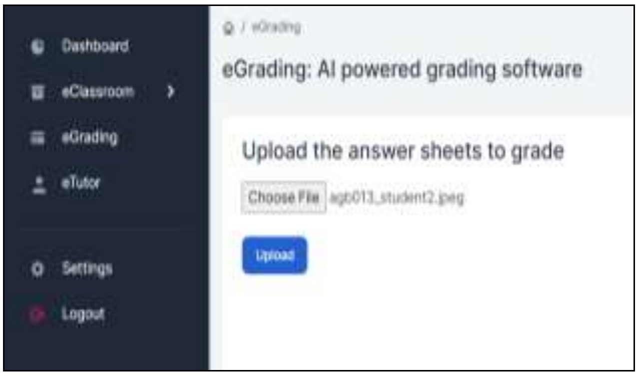

Fig -5: eGrading Demo Screen to upload answer sheet.

The first challenge in dealing with answer sheet images uploaded is dealing with different sizes, resolution, skewness, brightness, contract etc. This is where OpenCV (Computer vision open-source library) comes into handy. OpenCV can automatically adjust the size, convert into grey scale image. Once formatted answer sheet available, EasyOCR API can be called to read the image and interpret the text/answers. Once questions and answers are extracted, next step in the algorithm is comparing with pre-defined answers to determine correct and wrong answers and totaling the over score/grade.

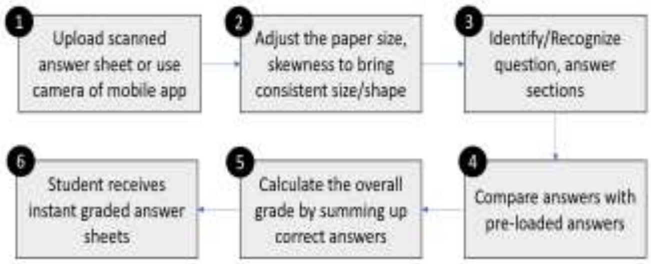

Fig -6: Overall eGrading solution

Below is the sample output of graded answer sheet that shows correct answers and grades.

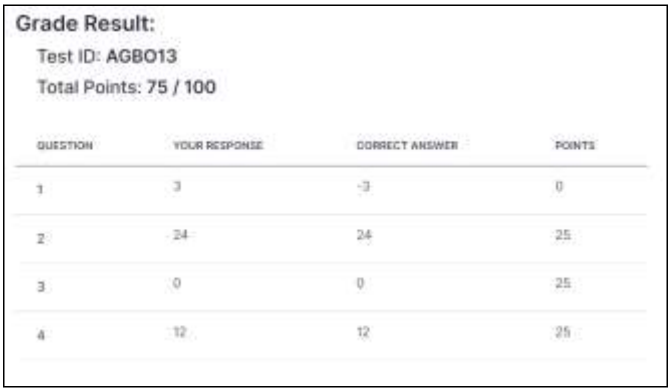

Fig -7: eGrading Demo of the results of a test/quiz after being uploaded.

Types of student answer sheets & support in traditional vs modern OCR methods.

Table -3: Capabilities/Limitations of traditional vs AI/ML based OCR solutions.

Types of Answer Sheets	Traditional OCR	AI/ML based OCR
True Or False	YES	YES
Multiple Choice	YES	YES
Fill in the blanks	Limited	YES
Free Response Questions	No	YES

The solution proposed assumes teachers input the pre-defined answers. With emerging tools like ChatGPT (OpenAI), this solution can be further improved by getting the answers generated by ChatGPT by calling OpenAI API. Beyond finding answers, AI technology can be used for classification of wrong answers to determine areas where students need to improve and further provides personalized learning.

4. CONCLUSIONS

eGrading using AI/ML accuracy can be greatly improved by leveraging AI/ML technology in addition to OCR. Apart from increasing accuracy it also supports grading of free response questions, adapting to the technology not only reduces workload on teachers but prepares for digital age.

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BIOGRAPHIES

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