Introduction  
The automatic recognition of numerical numbers and characters have the numerous applications including the verification of signatures in banking [1], name and address recognition from user submitted form [2] and recognition of clinical data [3]. The main agenda of these application is automatically recognizing the digits and characters from text document. To achieve this challenge, there is need to convert the text document in the scanned document or in the format that computer can understand. The text of the document may be a printed text or handwritten text. Hence, the information of the document can be categorized into two different categories i.e., handwritten or printed. In the schools, colleges and universities, the number sections for compulsory subjects are around 25-30 and each section normally have the 40 students. As the current educational system is based on mid term and final examination and each exam mostly based on 5-9 questions, the related supervisor or lecturers need to fill the marks sheet or enter in the portal more than 60000 times. In addition, the relative teacher also needs to calculate the total score of the student more than 60000 times. To finding the student names on the portal or marks sheet and fill the marks accordingly is also a very time-consuming task. The calculation of total scores more than 60000 times by the human increases the risk of false calculation or error. By viewing all of these hurdles and consumption of time and recourses, there is need of a mechanism that reduce the time and increase the efficiency of calculating the final score.

The alternative way of recognizing the marks on cover page or mark sheet is the optical mark recognition (OMR). The main objective of this technique is to extract the information from the specific location in the document [4]–[6]. The traditional OMR scheme basically worked with the light beam of scanner and the reflectivity of the light at the specific positions in the document are used to recognized the marks. The most popular and widely used application of OMR is the marking of students exams based on multiple choice questions. In this application, the HB or 2B pencil marks are used to fill the circle shaped bubbles on the exam sheet. The OMR application pass the scanner light and recognize the reflectivity from dark area. According to the reflectivity, it recognizes the selected option of multiple-choice question and also mark it accordingly. Majority of the OMR applications recognize the student-id or registration-id, student total score for multiple choice questions [7], [8] and automatically export the total score in the file with student registration id. OMR applications are very useful in educational premises and give the significant accuracy and efficiency in recognizing the marks. But the main disadvantage of the OMR application is that the OMR is just limited to the marking of multiple-choice questions. Alternatively, OMR can’t help to our all problems because most of the subjects examination could not be fulfill by the multiple-choice only. Normally, the exam paper is based on the multiple-choice, short questions and long questions and the student write the answer in the descriptive form rather than the filling of bubbles. Resultantly, the descriptive question needs to be understood by the teachers and marked them manually on the exam sheet. The manually marking of student exam paper and calculating the final score is not a big problem if the amount of student is not much high. But in real environment, the situation is totally changed. The total marking of exam and finding out the student ids in a big list will raise many problems.

To rescue this big problem, here is another technique refer as optical character recognition (OCR). OCR has the ability to recognize the typed text and handwritten text by converting the text document in the text image with the help of scanner. OCR systems are divided into two different categories labeled as offline recognition and online recognition. In the offline text recognition technique, the handwritten text document is converted into the machine-based image through scanning and then all the text is extracted from the image. While in the online recognition techniques, text information and numerical digits are typed from any typing device and then the recognition is made from the types document. The offline character recognition systems are more complex compare to the online recognition systems due to the different writing styles of users and noise during the writing of the text and scanning of the text document. Moreover, the text recognition systems are mainly worked on two different strategies labeled as segmentation then recognition and segmentation-based recognition. In the primary technique, the segmentation module returns the single character for recognition and the recognition module then recognize the single character. The major limitation of this technique is the false segmentation when the segmentation module does not extract the single characters accurately according to the defined rules. To increase the system's resilience, contextual data is frequently incorporated throughout the segmentation process. The best segmentation-recognition grade of the input picture must be expressed in the final choice under the second technique, which is based on a probabilistic premise. Typically, the segmentation module of the system generates a list of possibilities, and the recognition module subsequently assesses each assumption. The list is then postprocessed while taking the context into account. Although this method provides greater dependability than the previous one, its primary disadvantage is the computing work required to compare all the created possibilities. Additionally, different schemes including fragments, isolated characters, and linked characters must be distinguished by the recognition module. This technique allows either explicit segmentation based on cutoff algorithms [27], [7], or implicit segmentation where each pixel column is a candidate place for a cut [5], [22].

In this proposed work, we proposed the recognition module for the automatic recognition of handwritten grades on exam cover sheets. The recognition module will be based on the segmentation-based recognition technique. The recognition module will segment the marks on the exam sheet and then recognize the segmented area. For the recognition of text on the handwritten exam sheet, we proposed the Faster RCNN and Yolo V5 deep learning based models.

# Literature Survey

In recent years, the field of pattern recognition and image processing has focused on the idea of handwritten character recognition, and optical character recognition on handwritten scripts has gained widespread acceptance. This section presents a thorough study of the existing approaches in handwriting recognition systems that rely on different machine learning algorithms. Even though the recognition of printed material is now regarded as a solved problem, the identification of handwritten content is still a difficult task due to the high variance of different hand writing styles, font styles, font sizes, boldness of text and orientation of alphabets and digits among the different peoples. The interpretation of handwritten documents has been proposed using a variety of machine learning techniques. The automatic grading of handwritten responses and the identification of handwritten letters and numbers in multiple languages are only a few examples of the several handwriting recognition systems employing machine learning classifiers that are described in this section.

With the help of CNN, Brown [1] presented an automated method to score handwritten number responses on scanned answer sheets using the MNIST offline handwritten dataset. The accuracy of the CNN approximation of the student responses was 95.6%. In a study proposed by the author [2], a linear regression model was used for the for assessment of SAT test. The proposed study used the Kaggle dataset and converting the characters and digits into the features. The linear regression model showed the approximately 87% accuracy score. Multiple - choice questions answers were scored automatically in [3], allowing individuals to print and scan all of the answer sheets. Each answer sheet required 35 seconds of training time. The study [4] also proposed the random forest model for the recognition of handwritten student marks from the cover sheet. The proposed random forest model used the 3960 scanned documents for training and testing procedure and also produce the 89% accuracy. Srihari et al. [5] also proposed the marking scheme for the comprehensive types exams. They proposed the study used the handwritten 300 documents based on the essays and split the data with 50% ratio for training and testing data. For marking the handwritten essay, ANN classifier was used that present the approximately 87% accuracy score. Using the 13000 document Kaggle dataset as their starting point, Mahana et al. [6] created an automated method for scoring essays. Linear regression model was also used for extracting several features from the document of training set and got the 91.85% accuracy score after training.

An OMR system was launched by Saengtongsrikamon et al. [7] and implemented as an OMR machine using neural networks before being integrated into a scanner. With a 95.24% accuracy rate, this application recorded and graded the responses to multiple-choice questions.

# Methodology

## Faster RCNN

For the recognition of hand written marks on the cover page, we train the Faster RCNN model. For the recognition of the students marks custom generated dataset was used. Firstly, the dataset annotation was converted from the Yolo v5 format to Faster RCNN format. By following the preprocessing of the dataset, the train test slit function scikit learn library was used. It cutoff the dataset into training and testing batch with the ratio of 80% and 20% respectively. After the complete training of the Faster RCNN model, we got the 0.35% testing accuracy.