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Skew correction and image alignment for accurate region of interest detection in scanned exam papers

Ali Şentürk *[1]

[1]Isparta University of ApplieId Sciences, Faculty of Technology, Electrical and Electonics Department, Isparta, Türkiye

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Abstract: Accurate digit segmentation is a critical process in handwritten digit recognition. In structured documents, digits are written in predefined locations based on template files. One common example is exam papers, where students' identification numbers and evaluation grades are written in designated regions. However, in scanned documents, these locations are often misaligned due to skews, which negatively affects segmentation accuracy. This study proposes a skew detection and correction method combined with template matching based image alignment to improve digit segmentation for handwritten digit recognition. Unlike general-purpose methods, our approach focuses on structured exam templates, ensuring that numeric entries like student IDs and question grades are accurately extracted. Automating this process is particularly valuable for grading since manual entering scores for each question is a labor-intensive task, especially in large classes. Experimental results on 211 exam papers containing 3,407 handwritten digits show that 2,462 (72%) corrections were required due to misalignment. With the proposed alignment method, this number is reduced to only 333 (9.7%), demonstrating its effectiveness in template-based handwritten digit recognition.

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Taranmış sınav kağıtlarında doğru ilgilenilen bölge tespiti için çarpıklık düzeltme ve görüntü hizalama

Anahtar Kelimeler
Görüntü işleme
Çarpıklık düzeltme
Rakam bölütleme
Rakam tanıma

Makale geçmişi:
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Öz: Doğru rakam bölütleme, el yazısı rakam tanımada kritik bir süreçtir. Yapılandırılmış belgelerde, rakamlar şablon dosyalarına dayalı olarak önceden tanımlanmış konumlara yazılır. Yaygın örneklerden biri, öğrencilerin kimlik numaralarının ve değerlendirme notlarının belirlenen bölgelere yazıldığı sınav kağıtlarıdır. Ancak, taranan belgelerde bu konumlar genellikle çarpıklık nedeniyle yanlış hizalanır ve bu da segmentasyon doğruluğunu olumsuz etkiler. Bu çalışma, el yazısı rakam tanıma için rakam bölütlemesini iyileştirmek amacıyla şablon eşleştirme tabanlı görüntü hizalama ile birlikte bir eğrilik algılama ve düzeltme yöntemi önermektedir. Genel amaçlı yöntemlerin aksine, önerilen yaklaşımımız yapılandırılmış sınav şablonlarına odaklanmakta ve öğrenci numaraları ile soru notları gibi sayısal girişlerin doğru şekilde çıkarılmasını sağlamaktadır. Bu sürecin otomatikleştirilmesi, özellikle kalabalık sınıflarda her bir sorunun notunun elle girilmesinin zaman alıcı bir işlem olması nedeniyle notlandırma açısından büyük önem taşımaktadır. 3.407 el yazısı rakam içeren 211 sınav kağıdı üzerinde yapılan deneysel sonuçlar, hizasızlıktan kaynaklı olarak 2.462 (%72) düzeltme gerektiğini göstermektedir. Önerilen hizalama yöntemi ile bu sayı yalnızca 333'e (%9.7) düşürülerek, yöntemimizin şablon tabanlı el yazısı rakam tanımadaki etkinliği ortaya konmuştur.

1. Introduction

Although the use of digital writing is growing rapidly with the development of digital devices such as computers, mobile phones and tablets, handwriting continues to be widely used in many areas. One such

* İlgili yazar/Corresponding author: alisenturk@isparta.edu.tr

area where handwriting maintains its prominence is in educational exams.

In various official and standardized processes, quality systems necessitate the use of predefined templates for document creation. This approach provides consistency and clarity. One typical example of such a system is the design of exam papers used in educational institutions. Exam papers are carefully organized, with designated sections for essential information. For example, students must write their ID numbers in assigned areas. Similarly, scores for each question and the total exam score are written in specific locations on the documents.

In addition to standardization, the structured design of exam papers plays another critical role in maintaining the quality and accreditation of educational systems. Specifically, the scores written in specific areas for each question must be accurately recorded and entered into automation systems. This approach provides the extraction of detailed statistics for each question, such as average scores and difficulty levels. These processes are required for conducting analyses for the continuous improvement of examination quality and fairness.

However, as the number of students and the number of questions per examination increases, the processes become increasingly time-consuming. Manually entering scores for every question from each exam paper into a system is tiring. This approach also increases the chance of mistakes, especially when there are too many papers to handle.

The detection and extraction of handwritten digits from predefined template fields on examination papers could be a practical solution. The use of image processing and recognition technologies has the potential to save time by reducing the need for manual data entry. This approach has the potential to improve accuracy and allow educational institutions to focus more on analyzing results and implementing improvements rather than spending time on repetitive tasks.

Recent developments in machine learning have shown that convolutional neural networks (CNNs) are highly effective at predicting handwritten digits with a high accuracy [1]. CNN based models are widely used for handwriting recognition tasks because they can train to learn complex patterns and features directly from images. These models have great potential for automating the detection and recognition of handwritten digits in structured documents like exam papers.

However, achieving high accuracy in recognition depends on properly isolating handwritten digits from their surrounding areas. This step is especially important when working with official templates, where digits are often enclosed in borders for clarity. While these borders help during writing, they can interfere with digit recognition by adding unnecessary visual noise to the data.

Therefore, during segmentation, it is essential to isolate the handwritten digits from the surrounding borders. This ensures that the input given to the CNN model contains only the handwritten content, without any distractions from the template structure. By carefully isolating and preprocessing the relevant areas, the performance and reliability of the digit recognition system can be significantly improved.

While advanced image processing and machine learning algorithms can be employed to segment and identify handwritten digits, such complexity may not be necessary for template-based document processing. In cases where the structure of the document is constructed using a fixed template, determining the exact locations of the numerical entries within the template can be sufficient for effective segmentation and recognition. This approach simplifies the problem by using the predefined layout of the document, eliminating the need for complex computational models in certain scenarios.

However, some problems occur during the scanning process. Scanned documents are often misaligned due to small rotations and shifts when documents are placed into scanning devices. These issues can result in the regions specified in the template file does not align correctly with the corresponding areas in the scanned images.

To solve this problem, the scanned documents need to be processed to correct their alignment. Techniques such as rotation correction and alignment adjustments must be applied to transform the scanned document so that it matches the original template precisely. Therefore, the specified regions in the template can be accurately mapped to their locations in the scanned images, allowing accurate detection and extraction of handwritten digits.

This paper proposes a practical and efficient approach to addressing the challenges mentioned above, specifically for documents with predefined templates. The proposed method focuses on ensuring accurately correcting rotation and shifting to enable reliable detection and extraction of information from such template-based documents. The approach avoids the need for complex algorithms while maintaining high accuracy. This study provides a practical solution that can be used in automated systems, significantly reducing manual effort and improving the accuracy of data extraction processes. Unlike general-purpose skew correction methods, the proposed approach directly targets structured exam papers and their recurring layouts, offering a lightweight, template-driven alignment pipeline. This fills a gap in the literature by enabling high-accuracy digit extraction tailored for educational assessment systems.

2. Literature Review

As the advancement of the digital age, the conversion of physical documents into digital formats has become increasingly frequent. This transition not only facilitates the storage and sharing of information but also enables advanced processing and analysis of document content. A key technology in this area is Optical Character Recognition (OCR), which has been extensively utilized to extract text information from scanned documents and make their contents digitally accessible. OCR is used in many fields such as archiving historical documents, automating administrative tasks and enabling data-driven analyses.

Achieving high accuracy in OCR requires several preprocessing steps for effective recognition. Common techniques include [2]:

- Filtering: Removing unwanted noise or distortions from scanned images while preserving the essential features of the text and document structure.
- Morphological Operations: Improving the structure of text elements by removing noise or filling gaps within characters.
- Thresholding: Converting grayscale into binary format to distinguish the text against the background.

These preprocessing steps are critical for enhancing the clarity and structure of scanned images, enabling OCR systems to operate more effectively [3],[4].

Another important preprocessing method is skew correction. This process involves correcting angular deviations in scanned documents to ensure proper alignment of text and regions. This process is important because even small angular misalignments can significantly affect the performance of OCR and other document processing techniques. Skewed text can lead to errors in character segmentation, template matching and region detection, greatly reducing the accuracy of extracted data.

To solve this issue, various algorithms have been developed to detect and correct skew. Common methods include the use of the Hough Transform, projection profiles and contour analysis. These methods are designed to estimate the skew angle and adjust the orientation of the document to its correct position.

Sun and Si [5] proposed a fast algorithm for skew correction in printed documents, using gradient orientation histograms to estimate the skew angle. Their method corrects skew via rotation and parallelogram fitting, demonstrating accurate results across diverse document types.

Al-Shatnaw and Omar [6] indicated that skew detection and correction as critical for reliable segmentation and feature extraction in document analysis. They proposed a method which fitting text within an arbitrary polygon and derive a baseline from its centroid is proposed, proving to be efficient, fast and robust against noise, font variations and resolution differences.

Fan et.al [7] introduced the Rectangular Active Contour model for skew detection, which uses global image features and shape constraints. The method demonstrates high accuracy across complex document layouts with diverse content while detecting rectangular content regions.

Konya et al. [8] proposed a generic and scale-independent algorithm for skew detection, capable of accurately identifying the global skew angle of document images. The method was further extended for Roman script documents. The algorithm was reported to achieve high accuracy in experiments.

Makridis et al. [9] proposed an adaptive technique for global and local skew correction in colored documents, which can also be applied to grayscale and binary documents. The method involves four key stages: color reduction, text localization, document binarization and skew correction. Extensive experiments conducted on scanned color book covers and grayscale scanned newspapers to demonstrate the technique's effectiveness to detect and correct skewness.

Meng et al. [10] proposed a general-purpose method for estimating skew angles in document images by using a variety of visual suggestions from local image regions rather than relying solely on text lines. The approach utilizes Radon transform to extract visual cues, iteratively rejects outliers using a floating cascade and employs a bagging estimator to combine local estimations.

Papandreou and Gatos [11] introduced a skew detection method that utilizes vertical projections combined with a bounding box minimization criterion, rather than the conventional horizontal projections. This approach is particularly effective due to the prevalence of vertical strokes in Latin characters. Additionally, the technique is robust to noise and warping, making it suitable for early examples of printed documents.

Brodi et al. [12] proposed a method for text skew estimation in printed documents. Main steps of the method are removal of redundant data, establishment of connected components representing convex hulls around text, enlargement of the components using morphological erosion and removal of the largest component to estimate the text skew.

Papandreou et al. [13] proposed a skew detection method that combines horizontal and vertical projection profiles using the technique of minimum bounding box area. This approach effectively handles a variety of document types, including early examples of printed documents and multi-column layouts. The approach also improved performance in optical character recognition tasks.

Boukharouba [14] proposed a technique for skew correction and baseline detection in Arabic documents, utilizing a randomized Hough transform to detect skew angles. By focusing on the lower baselines of text lines and using y-intercept histograms, the method effectively extracts baselines and corrects skewness in skewed document images. The approach is stated to be applied to various languages by text line extraction.

Rezaei et al. [15] introduced an adaptive document image skew estimation algorithm that leverages existing features and supervised learning to enhance estimation time and accuracy. Training the algorithm once on a set of training images leads to faster performance. Additionally, it achieves higher accuracy through adaptive feature selection and learning, making it effective for small skew angles.

Köksal [16] proposed a skew detection method that forms rectangular blocks and uses their centroids to estimate the skew angle. This method is independent of the script used and supports a wide range of scan intervals, offering advantages in both speed and accuracy. In the study the proposed approach is reported to outperform other popular methods in terms of speed and achieved the second-highest accuracy.

In [17], de Elias et al. proposed a method for correcting skew, translation, scale and alignment in optical mark documents, using a base document as a reference. The approach leverages a pattern matching algorithm to identify key points for image transformation, allowing for minimal formatting and enabling nonexperts to create optical mark documents forms with ordinary software and scanners.

In [18], Boudraa et al. introduced a novel skew detection and correction technique that combines Morphological Skeleton and the Progressive Probabilistic Hough Transform (PPHT). This approach reduces data by preserving only central curves, then applies PPHT to identify lines from which the global skew angle is calculated. The method was reported to be highly accurate and effective across a range of document types, including diverse languages, orientations and complex layouts.

Chettat et al. [19] proposed a method for skew angle estimation and correction in scanned documents, addressing the challenge posed by graphic zones that often interfere with text skew estimation. Their approach combines local binarization, horizontal smoothing via the Run Length Smoothing Algorithm, contour detection and the Hierarchical Hough Transform to ensure accurate and efficient skew detection even if there are many graphics in the document.

Ahmad et al. [20] presented another method for skew detection and correction in scanned documents by utilizing Probabilistic Hough Transformation for initial line detection and clustering parallel lines to determine the skew. Their method was tested on multiple datasets and demonstrates high accuracy and noise resistance which is reported to be suitable for both Latin and Arabic scripts and enhances Optical Character Recognition.

Pham et al. [21] proposed a skew estimation technique that uses Adaptive Radial Projection on the 2D Discrete Fourier Magnitude spectrum to determine the dominant skew angle in scanned document images. They reported that the method represents a significant improvement over traditional Fourier based methods for skew estimation and demonstrates higher performance compared to existing techniques.

Rocha et al. [22] proposed a skew angle detection and correction method based on RGB gradient, which is designed to work efficiently across various document types. The method enhances document layout analysis and optical character recognition tasks by improving accuracy in skew correction. Their approach presented robust performance in diverse text orientations and imperfectly scanned documents.

For a broader understanding of general methods used in document skew detection and correction, Rehman and Saba [23] provide a detailed analysis of various techniques, highlighting common challenges and potential solutions, while Rezaei et al. [24] focus on the skew detection of scanned documents, addressing the fundamental concepts and algorithms. Furthermore, comprehensive surveys on document image skew detection from Biswas et al. [25] and Inunganbi [4] offer detailed discussions on existing methods, experimental benchmarks and comparative analyses. These works collectively serve as valuable resources for understanding both general approaches and specific advancements in the field.

While previous studies have achieved significant progress in general-purpose skew correction, few have focused specifically on structured educational exam papers where field-level accuracy is the main focus. Our work differs by offering a practical, template-based solution specifically designed for the recurring layout patterns found in exam grading documents, thereby bridging the gap between skew correction techniques and domain-specific applications in education.

3. Proposed Method

As highlighted in the introduction, predefined templates are commonly utilized in various official documents, including exam papers used in educational institutions. These templates typically include a boxed section at the top containing information about the organization, such as its logo and a statement regarding the purpose of the template. Additionally, specific regions are designated for students to write their ID numbers in predefined areas. Similarly, the grades for each individual question are recorded in allocated sections and the total examination score is calculated and written into a specific location on the documents. A similar approach is observed in the exam documents used at Isparta University of Applied Sciences, as illustrated in Figure 1.

The topmost section of the template shown in Figure 1, enclosed within a red rectangle to highlight the skewness present in the scanned document. To accurately identify specific areas, such as the ones for student ID digits, individual question grades and the total grade, applying skew correction is essential. If the number of documents is fewer, this process can be performed manually. However, when dealing with a large number of documents, it becomes essential to automate this task.

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Süre: 40 dakika | 29/11/2024, 15:30, No'lu Salon

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Güz ✓ Bahar | Sınıfı 4 | Öğretimi

Öğretim Elemanı Adı Soyadı: Dr. Öğr. Üyesi Ali ŞENTÜRK

Soru No	Soru Puanı	Aldığı Puan	Ölçülen Ders Kazanımları ve Kazanımlara Yüzdelik Katkısı				
			1. Kazanım	2. Kazanım	3. Kazanım	4. Kazanım	5. Kazanım
1	15			100			
2	25		20	20	10	25	25
3	20		10	20	50	10	10
4	40		30	20	10	20	20

Figure 1. Exam paper template used in Isparta University of Applied Sciences

The following systematic approach proposed for skew detection and correction which ensures accurate alignment of the scanned document images. This method identifies the skew angle of the document and applies the necessary corrections to enable the subsequent segmentation and analysis processes. The method involves two main steps: detecting the largest topmost contour of the document and calculating the rotation angle for the skew correction.

3.1. Detection of the Topmost Largest Contour

The initial step is to preprocess the document image to identify the largest topmost contour, which typically represents the document's header. The image is converted to grayscale and binarized for better contrast by applying thresholding. Morphological erosion with a 5 by 5 kernel is then applied to remove noise, followed by edge detection using the Canny edge detection algorithm. The lower and upper threshold values of Canny is empirically selected as 50 and 150. Contours are identified from the edges and a filtering process returns only the largest contour based on the widths and positions. These filtered contours are sorted by their vertical position to identify the topmost contour which is the contour of the header of the document. The resulting images of the process are shown in Figure 2.

3.2. Skew Angle Calculation and Correction

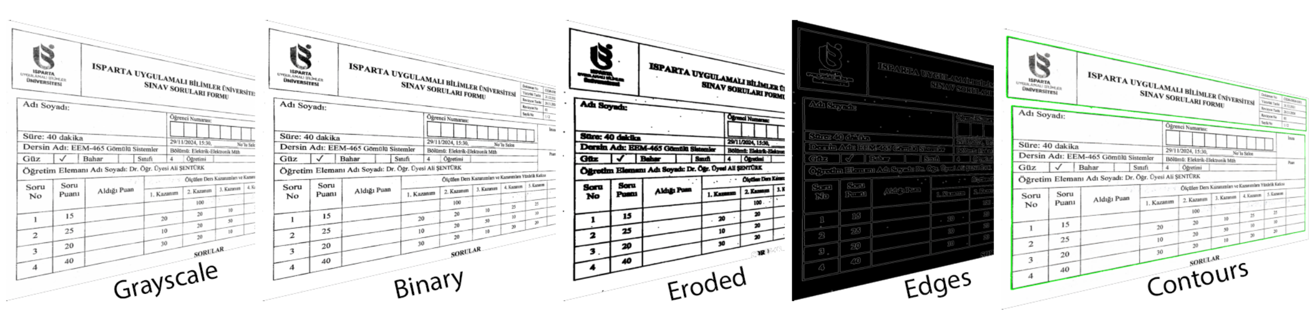

Figure 2. Preprocessing of the documents for skew detection

Once the topmost largest contour is identified, a minimum area rectangle is fitted around it to approximate the document's boundaries. Let the vertices of the rectangle be represented as:

$$V = \{(x_1, y_1), (x_2, y_2), (x_3, y_3), (x_4, y_4)\}. \tag{1}$$

The rectangle's corner points are sorted by their y-coordinates to identify the upper two points:

$$V_{\text{sorted}} = \text{Sort}(V, \text{by } y) \tag{2}$$

where the first two points of V_{sorted} correspond to the upper edge points:

$$U = \{(x_l, y_l), (x_r, y_r)\}. \tag{3}$$

Using the coordinates of the edge points, the slope m is computed as:

$$m = \frac{y_r - y_l}{x_r - x_l}. \tag{4}$$

The skew angle θ is calculated as:

$$\theta = tan^{-1}(m). \tag{5}$$

If the edge is vertical ($x_l = x_r$) the skew angle θ is $\pi/2$.

After determining the skew angle, the rotation transformation matrix M for rotating the document image around a center point (x_l, y_l) is defined as:

$$\begin{bmatrix} \cos\theta & -sin\theta & (1 - cos\,\theta)\cdot x_l + sin\,\theta \cdot y_s \\ \sin\theta & \cos\theta & (1 - cos\,\theta)\cdot\ y_l - \sin\theta \cdot x_s \end{bmatrix} \tag{6}$$

The skew of the document is corrected by applying the rotation transformation using M, resulting in a properly adjusted image.

3.3. Alignment of Images

After the skewness correction step, to ensure consistent alignment across multiple scanned document images, a template matching-based alignment approach is employed. The process consists of two main steps: template region detection and image shifting for alignment.

The template region, which is detecting the topmost largest contour is detected after the skew correction of the template image. The template region from the template document is cropped and converted to grayscale. This template region is compared to the other skew corrected images using the template matching algorithm with the Normalized Cross-Correlation method. The location of the best match is identified and the positional shift between the template and the scanned image is calculated.

Once the displacement in both x and y directions are computed and if there is a shift is available, a translation matrix is constructed to adjust the document accordingly:

$$M = \begin{bmatrix} 1 & 0 & S_x \\ 0 & 1 & S_y \end{bmatrix}. \tag{7}$$

where S_x is the shift amount in the x direction and S_y is the shift amount in the y direction. The scanned document image is transformed using an affine transformation with the transfer matrix in Equation-9, which corrects its position to match the reference template.

4. Results

The skew correction and image alignment methods described in this study were implemented in a Python-based program and applied to This program operates in two main stages. In the first stage, the regions of interest (ROIs) within the template file are identified. Since template files also may exhibit skew, automatic skew angle detection and correction are performed at this stage. Specifically, after loading the template image, the largest topmost contour is detected using the procedure outlined in the Materials and Methods section and the necessary skew correction is applied. After this correction, the ROIs are accurately marked, as shown in Figure 3, with a rotation of 0.38275 degrees, using the top-left corner of the largest contour as the center of rotation.

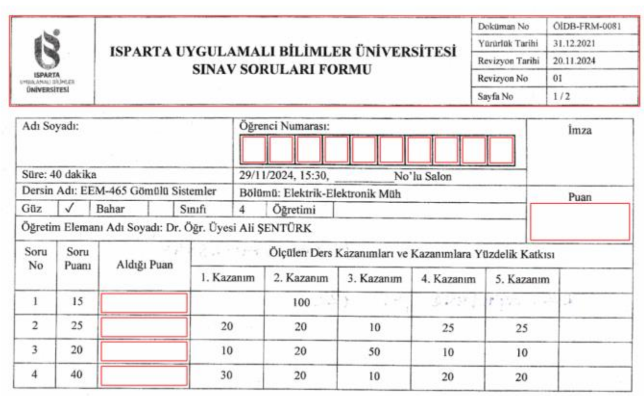

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Figure 3. Skew corrected template file with marked ROIs

In the second stage, the segmentation of digits within the ROIs in scanned student exam documents is performed. First, skew correction is applied to the student image, the image alignment process is utilized. Figure 4 to 6 present examples of ROIs before and after these procedures. Figure 4 illustrates the regions on the raw document image. Figure 5 displays the skew-corrected image with the identified regions marked, while Figure 6 shows the final skew-corrected and image-aligned document. Some regions in the images have been intentionally corrupted to protect privacy.

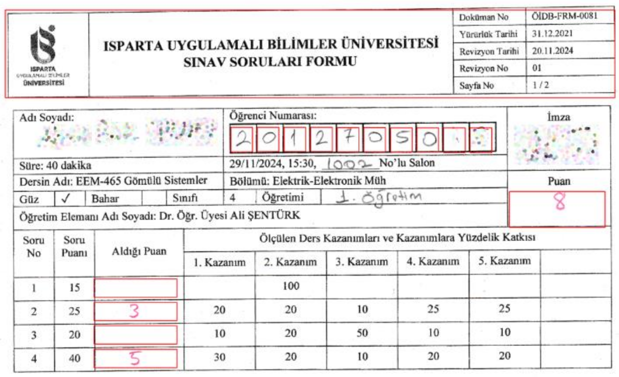

Figure 4. ROIs on the raw image

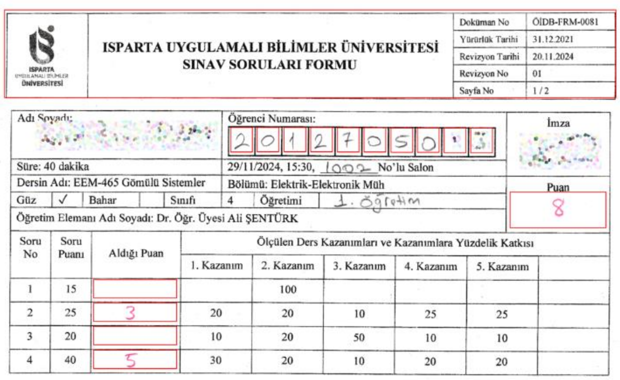

Figure 5. ROIs on the skew corrected image

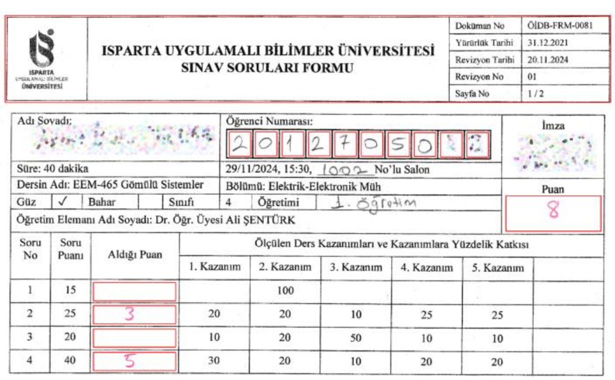

Figure 6. ROIs on the aligned image

4.1. Evaluation of Prediction Accuracy and the Effect of Skew Correction

Table 1 summarizes the prediction performance by comparing the predicted digits with the ground truth, focusing specifically on cases where both the digit value and its position match exactly. The evaluation was conducted on 211 document images scanned at 200 dpi, with a total of 3,407 digits expected to be predicted.

The table also highlights the critical role of skew correction in improving prediction accuracy for scanned exam documents. In raw document images, digit segmentation often includes the borders of the designated writing regions, which can lead to over-segmentation and the detection of additional, unintended digits.

To better quantify prediction performance in such cases, the Levenshtein distance is employed. This metric measures the minimum number of single character edits (insertions, deletions, or substitutions) required to transform the predicted sequence into the ground truth [26]. As this study focuses on facilitating accurate digit entry, Levenshtein distance offers a suitable and informative similarity measure.

Moreover, to allow for comparisons across digit sequences of varying lengths, the Levenshtein distance is normalized. Inspired by the normalized generalized Levenshtein distance proposed in [27], we define a simplified Normalized Edit Similarity (NES) as:

$$NES(X, P) = 1 - \frac{Levenshtein(X, P)}{\max(|X|, |P|)} \quad (8)$$

where X denotes the ground truth string, P denotes the predicted string, and $|\cdot|$ represents the string length. This normalization bounds the similarity score between 0 and 1, with values closer to 1 indicating higher similarity.

Table 1. Comparison of prediction performance between raw and aligned images.

	Raw images	Aligned images
Correct Predictions	1,412	3,069
Accuracy	41.44%	90.08%
Levenshtein distance	2462 (72%)	333 (9.7%)
NES	0.613	0.928

These results demonstrate that skew correction significantly improves both positional and value accuracy of digit predictions, leading to a more reliable and efficient automated digit recognition system.

5. Conclusion

In this study, skew detection and correction for template-based document images such as scanned student exam papers is proposed. The proposed skew detection, correction method along with image alignment based on template matching was evaluated on student exam documents to detect predefined regions where there are handwritten digits such as student IDs and grades from question and total grade. The effectiveness of the proposed methods for alignment assessed by comparing the raw images (unaligned) with the aligned images after skew correction and alignment. The number of correct digit predictions significantly increased after alignment, rising from 1,412 in raw images to 3,069 in aligned images, out of a total of 3,407 digits, where both the digit value and its position were correct.

A notable issue in the raw images was the high Levenshtein distance of 2,462, indicating substantial deviation from the ground truth due to segmentation errors. After alignment, this value was reduced to 333.

Overall, the results indicate that the skew correction and image alignment process significantly improves digit segmentation and recognition performance, minimizing the impact of misalignment-related errors in automated handwritten digit prediction tasks.

In conclusion, this study presents a practical solution for skew detection and alignment in template-based exam papers, enabling accurate digit recognition and significant improvements in segmentation quality. The contributions are (i) we designed a lightweight, reproducible pipeline for digit extraction in structured documents, and (ii) we empirically demonstrate its impact in real scanned papers.

As future work, we plan to extend the proposed method to further improve digit recognition by addressing the - residual lines around predefined fields. Specifically, we aim to develop a graphical user interface application that automatically detects these residuals and allows users to manually annotate lines surrounding digit regions for cases missed by detection. These annotations will then be used to train an automated model, such as a transformer-based architecture, to remove such artifacts programmatically. Eliminating these residuals is expected to further increase digit recognition accuracy by reducing noise around the digits.

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