Academic Attendance System

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***Özetçe* —Günümüzde eğitim süreçlerinin dijital bir dönüşümden geçtiği bu dönemde, sadece öğrenciler için değil akademisyenler için de birçok yenilikçi girişim geliştirilmiştir. Bu proje, geleneksel yoklama sistemlerine alternatif bir çözüm sunarak akademisyenlerin yoklama yönetimini kolaylaştırmayı hedeflemektedir. Yoklama kağıtlarını dijital ortama aktaran ve imzaları görüntü işleme teknikleriyle doğrulayan bu sistem, öğrenci devamsızlıklarının kaydında doğruluk ve verimliliği artırmaktadır. Proje ayrıca, belirlenen kriterlere göre akademisyenlere öğrencilerin devam durumları hakkında uyarılar sağlayan bir bildirim modülü de entegre etmektedir. Bu makale, bu yenilikçi yaklaşımın geliştirilmesi ve uygulanması üzerine tartışmalar sunmakta, kullanım kolaylığı, maliyet verimliliği ve mevcut yöntemlere kıyasla güvenlik gibi avantajlarını vurgulamaktadır.**

Anahtar Kelimeler—Dijital dönüşüm, eğitim teknolojisi, yoklama yönetimi, görüntü işleme, imza doğrulama, mobil arayüz, akademik verimlilik, veri güvenliği.

***Abstract*—In today's era of digital transformation in educational processes, numerous initiatives have been developed to benefit not only students but also academics. This project presents an alternative solution to traditional attendance systems, aiming to simplify the attendance management for academics. By digitizing attendance sheets through captured images and employing image processing techniques to verify signatures, this system enhances accuracy and efficiency in recording student attendance. The project also integrates a notification module, which alerts academics about students' attendance based on predefined criteria. This paper discusses the development and application of this innovative approach, highlighting its advantages in terms of ease of use, cost-efficiency, and security compared to existing methods.**

Keywords—Digital transformation, educational technology, attendance management, image processing, signature verification, mobile interface, academic efficiency, data security.

I. Introduction

This paper discusses the digital transformation of educational processes with a focus on streamlining administrative tasks and enhancing the management capabilities of academics in Turkish universities. Traditional attendance systems, which predominantly rely on paper-based signature collection, are time-consuming and susceptible to inaccuracies and fraudulent activities. Our proposed system aims to revolutionize this archaic method by automating the digitization of attendance data from photographed attendance sheets, thereby reducing manual labor and increasing the reliability of records. The implementation of signature comparison algorithms and a user-friendly mobile interface not only provides a secure method for monitoring attendance but also eliminates the need for physical storage of sensitive data, thus enhancing both privacy and security. This introduction outlines various existing systems, pinpoints their shortcomings, and demonstrates how our innovative approach sets a new benchmark for efficient, secure, and user-friendly academic attendance management.

II. Background and Motivation

In the majority of Turkish universities, student attendance is recorded using a paper-based method wherein academic staff manually collect and verify signatures on attendance sheets. This conventional approach necessitates the laborious task of counting signatures and subsequently entering this data into a system, which is both time-intensive and prone to inaccuracies. Furthermore, it is vulnerable to the risks associated with fraudulent signatures. Our proposed solution seeks to address these challenges by introducing an automated attendance tracking system. By utilizing advanced image processing techniques to digitize signature sheets, our system significantly minimizes manual input and enhances the overall accuracy and integrity of the attendance records.

III. Literature Review

This section of the article provides a comprehensive review of existing research and methodologies pertaining to attendance management systems, highlighting the advancements and limitations that have informed the current project's approach.

In traditional attendance systems, students sign their names on a circulating paper list during class. This manual process is labor-intensive for academics who must verify and record each entry, making it prone to human error.

RFID-based facial recognition systems [1] enhance tracking by using RFID technology to record students as they enter and exit the classroom. Although this method offers accurate attendance data, it involves high installation and maintenance costs and can be influenced by environmental factors such as changes in facial features.

Iris recognition systems [2] require students to have their iris patterns scanned and matched against a database upon entering the classroom. This method emphasizes security, as iris patterns are sensitive biometric data, but it also necessitates robust protections against unauthorized access.

The SEAts Mobile App [3] employs QR codes and Bluetooth for attendance monitoring. Students either scan a QR code or are detected via Bluetooth signals. This approach faces challenges in technological accessibility for students and compatibility issues with older Bluetooth versions.

Finally, a project aimed at simplifying traditional signature-based attendance systems utilizes neural networks for signature comparison [4]. Student signatures are stored in a database and compared with new signatures. However, storing sensitive data like signatures poses significant security concerns.

IV. Technical Implementation and Development Tools

The mobile application for this project utilizes the React Native framework to support both iOS and Android systems, benefiting from its cross-platform capabilities and alignment with our performance and portability needs. Our familiarity with React Native further influenced its selection, with development facilitated by Expo Go for handling platform-specific configurations, using Visual Studio Code as the integrated development environment.

The signature comparison feature is developed in Python, leveraging its robust libraries suited for AI and deep learning. Python's straightforward syntax allows for efficient model prototyping with key libraries including OpenCV for image processing, NumPy for numerical tasks, and TensorFlow and Keras for deep learning, ensuring a streamlined development process.

For database management, MongoDB is used for its scalability and flexibility. As a non-relational, document-based system, it allows for efficient data modeling and is ideal for managing the increasing volume of attendance data, storing information in JSON-like documents which simplifies application development.

V. Appication Modules

The mobile application facilitates course management and attendance tracking for faculty members, allowing them to add and manage their courses efficiently. By entering key details such as course name, code, and hours, instructors can set specific attendance protocols for each class. This capability ensures that instructors can continually monitor student absences and weekly attendance rates to keep classroom performance up-to-date. Moreover, the app automates the digitization of attendance sheets using image processing technologies, verifying student attendance through signature comparison and enhancing academic integrity by alerting instructors to potential signature fraud.

Additionally, the application supports proactive classroom management by enabling instructors to send tailored alerts and absence reports based on predefined attendance criteria. This feature allows for the automatic sending emails to students when necessary, aiding faculty in maintaining effective classroom management and encouraging students to adhere to their academic commitments. Through these functionalities, the app not only simplifies administrative tasks but also helps uphold the standards of academic responsibility and integrity.

VI. Design for Image Processing

The primary step in detecting similarities between two signatures involved the creation of a Convolutional Neural Network (CNN) model. This model was trained with horizontally concatenated images of processed signatures. The categorical cross-entropy function was used as the loss function, classifying the images into two categories: 0 (original) and 1 (forged). However, as this model performed classification rather than quantifying similarity based on vector angles, it did not fully meet the project's objectives. Consequently, a Siamese Neural Network (SNN) model was employed, better suited for comparing handwritten signatures and quantifying their similarity.

A. Dataset Design

The dataset used for model training comprises authentic handwritten signatures from real individuals. Each individual's set contains a defined number of original and forged signatures. To enhance the model's accuracy and generalization capabilities, meticulous attention was given to data collection, labeling, and segmentation.

The collection phase involved gathering signature images from multiple sources: the CEDAR research center [5], the Signature Verification Dataset available on Kaggle [6], and additional signatures sourced from the environment, culminating in a diverse dataset of signatures from 115 individuals, which included 24 original and forged signatures for 63 individuals and 12 for the remaining 52 individuals. For labeling, the comparison results of these signature images were methodically recorded in a CSV file, organized into three columns: the first two columns indexed the signature images compared, and the third column contained the comparison result—0 if both signatures were original from the same person, and 1 if one was original and the other forged. In the data separation phase, the contents of this CSV file were divided into three clusters for machine learning purposes—70% of the data was allocated for training, 15% for validation, and 15% for testing, ensuring each set maintained equal proportions of 0 and 1 results. These segmented files are earmarked for use in subsequent image processing steps, facilitating effective training and validation of the model.

B. Software Design for Image Processing

Image processing is critical in preparing the data for training AI models, aiming to reduce imperfections in the data and enhance its quality for feature extraction. Various techniques were applied to the signature images using the Python-based OpenCV library, tailored to each signature image detailed in the first two columns of the CSV file. These techniques, applied sequentially to each image, transformed raw images into cleaner, more consistent formats suitable for model training.

- **Grayscale:** Images were converted to grayscale using OpenCV, focusing only on intensity and brightness, which are essential for recognizing signature shapes.
- **Resizing:** All images were resized to 128x128 pixels. Other sizes like 64x64 and 224x224 were tested, but

128x128 was chosen for its balance between quality and computational efficiency.

- **Gaussian Blur Application:** This technique applied a 3x3 Gaussian filter to smooth the images, reducing noise and unwanted sharp transitions, thus focusing the model on fundamental features.
- **Adaptive Thresholding:** Using the ADAPTIVE-THRESH-GAUSSIAN-C parameter in OpenCV, this method adjusted the threshold based on local image properties, providing consistent results regardless of lighting variations.
- **Normalization:** Finally, pixel values were normalized to a range of 0 to 1, speeding up the model training process and enhancing the model's generalization ability while reducing the risk of overfitting.

C. Model Architecture

In the field of deep learning, the Siamese Neural Network (SNN) architecture, which incorporates twin sub-networks of identical configuration, has proven effective, particularly in signature verification tasks. Unlike traditional Convolutional Neural Networks (CNN) that generally consist of convolutional layers for feature extraction, non-linear layers for applying activation functions, and pooling layers for reducing spatial resolution, SNN utilizes two identical CNNs. These sub-networks share parameters and weights and are combined through a distance metric, enabling precise feature extraction from two input signature images. The distinction between the signatures is then assessed using the Euclidean distance, which calculates the root of the sum of squared differences between elements of two real-valued vectors. A smaller Euclidean distance indicates greater similarity between the signatures, suggesting that they are likely from the same individual. This approach has demonstrated reliability and consistency in training and prediction phases of the model, making it a preferred choice for this project.

D. Metrics Used in Model Compilation and Training

In the training of our Siamese Neural Network (SNN) model for signature verification, we employed a contrastive loss function, a popular choice for such networks. This function aims to minimize the distance between similar items while maximizing the distance between dissimilar ones, thereby enhancing the model's ability to differentiate between distinct examples.

Additionally, the F1-Score, a critical metric in our model evaluation, considers both precision and recall. Precision measures the ratio of correctly predicted positive observations to the total predicted positives, while recall indicates the ratio of correctly predicted positives to all actual positives. The F1-Score, being the harmonic mean of precision and recall, provides a balanced view of the model's predictive accuracy and consistency. These metrics, derived from the confusion matrix—which categorizes predictions into true positives, false positives, true negatives, and false negatives—offer a comprehensive understanding of the model's performance across different scenarios.

E. Attendance Sheet Template Design

In the image processing steps for the template, a sample image was created by taking a photo of the attendance sheet. Various image processing techniques were applied on this image.

- To process the attendance sheet, the photo is first resized to 1750x1250 pixels to maintain a consistent aspect ratio of approximately 1.41, similar to A4 size, ensuring clarity for OCR reading of student numbers. The image is then converted to grayscale to reduce processing load and eliminate irrelevant color information, improving signature detection efficiency.
- A Median Filter is applied to reduce noise and smooth transitions, which is crucial for subsequent steps like thresholding and edge detection. This filter effectively removes salt and pepper noise by replacing each pixel value with the median value of its neighborhood.
- Adaptive thresholding is utilized to generate consistent binary images across varying lighting conditions using the adaptive Gaussian method. This step classifies each pixel based on the weighted average of its neighborhood, enhancing detail detection in signatures.
- Edge detection is conducted using the Canny algorithm, which employs a dual-threshold technique for enhancing significant edges. Morphological operations like dilation and erosion are applied to refine these edges.
- Line detection follows, using the Probabilistic Hough Line Transform to identify and delineate horizontal and vertical lines, essential for defining student number and signature areas. Detected lines are adjusted for any interruptions caused by noise, low contrast, or complex backgrounds using geometric calculations based on the slope and intercept.

The operations performed after the template design is made are given under the following headings.

1) Contour Detection in the Attendance Template: In the attendance template processing, contours of student numbers and signature areas are detected using the findContour function in OpenCV. The detected contours are organized by coordinates, allowing precise identification and filtering based on specific dimensions. Student number areas are first identified and read using OCR, where Easy OCR is preferred due to its superior accuracy. Signature areas are subsequently isolated, cropped, normalized, and resized to ensure consistent analysis and integration into the attendance system, enhancing the accuracy and reliability of the attendance management process.

2) Absence Detection Process: The absence detection in the attendance template involves analyzing the data from designated signature areas. Initially, each signature area is checked to determine if it is empty by calculating the average pixel value of the region. Areas with an average pixel value above a specific threshold (indicating a color close to white) are considered empty. For non-empty regions, the presence of a signature or an absence symbol ("/") is identified. The average pixel values for absence symbols are calculated as 0.98295 and for signatures as 0.88601, allowing for differentiation based on the established threshold value. This distinction is crucial for updating weekly attendance statuses and comparing signatures. The process ensures accurate and reliable parsing of the attendance template data, enabling straightforward tracking and analysis of student attendance over a seven-week period, updating absence information from 1 to 0 in weeks where an absence symbol is detected.

3) Signature Comparison Algorithm: The signature comparison algorithm evaluates similarities between signatures and forms groups based on a specified threshold value. Initially, each signature starts in its own group with a score of 1. In the first step, the first signature is compared with all others; signatures that exceed the similarity score threshold have their scores added to the first signature's score and are then set to zero, preventing further comparisons. Subsequently, the first non-zero scoring signature is compared with other remaining signatures, grouping those that exceed the threshold and removing them from further comparisons. This process continues until all signatures have been evaluated. This method efficiently conducts only necessary comparisons, significantly reducing complexity and processing time. Additionally, to avoid issues with personal data rights, the largest group is considered the original signature, allowing each new set of signatures to be independently evaluated without the need to store personal data.

VII. Experimental Results

This chapter discusses the training and performance evaluation of the model, utilizing the dataset and metrics designed in earlier stages.

A. Model Training

The model training was conducted based on the architecture specified for the dataset. Before the training process, the model was compiled with a contrastive loss function and metrics. An early stopping criterion was implemented during training to minimize the risk of overfitting. Upon completion, the model's performance was evaluated on the validation and test datasets.

B. Model Performance

In this section, experimental results and analyzes on the performance of the developed model are presented. The results obtained using different experiments and parameters are summarized in Table 1.

Table 1 Model Comparison

Deneme	Opt.	Kayıp Fonk.	Batch	Epoch	Eğitim	Doğr.	Test
1	RMSProp	Bin. Cross.	128	10	0.702	0.677	0.673
2	RMSProp	Contr. Loss	128	10	0.892	0.885	0.887
3	Adam	Bin. Cross.	128	10	0.843	0.838	0.841
4	Adam	Contr. Loss	128	10	0.930	0.924	0.918
5	Adam	Contr. Loss	256	15	0.996	0.995	0.998

C. Evaluation of Model Prediction Outputs

In this section, the results from comparing randomly selected pairs of signatures from the training, validation, and test datasets are presented. Each comparison results in a Euclidean distance-based similarity score. A threshold value of 0.65 for the Euclidean distance was set, implying a similarity score threshold of 0.7, calculated from the given formula. This method assesses the model's ability to accurately measure the likeness between two signature images.

VIII. Conclusion

This paper has presented an advanced digital attendance system that enhances the process of monitoring and recording student attendance through the integration of image processing technologies and a mobile application. By automating the verification of signatures from digitized attendance sheets, our system significantly reduces potential errors and fraudulent activities, providing a robust solution to common challenges in educational administration. Future work will focus on incorporating more sophisticated machine learning algorithms to improve signature verification accuracy and exploring blockchain technology to ensure data integrity. This research offers a valuable blueprint for educational institutions aiming to leverage technology to streamline administrative tasks, setting a foundation for ongoing innovation in educational technology.

References

[1] M. S. Akbar, P. Sarker, A. T. Mansoor, A. M. Al Ashray, and J. Uddin, "Face recognition and rfid verified attendance system," in *2018 International Conference on Computing, Electronics Communications Engineering (iCCECE)*, 2018, pp. 168–172.

[2] K. O. Okokpujie, E. Noma-Osaghae, O. J. Okesola, S. N. John, and O. Robert, "Design and implementation of a student attendance system using iris biometric recognition," in *2017 International Conference on Computational Science and Computational Intelligence (CSCI)*, 2017, pp. 563–567.

[3] S. Software. (2023) Education success platform. [Online]. Available: https://www.seatssoftware.com

[4] H. Abu Bakar, "Signature recognition system for student attendance system in utp," 2004.

[5] M. J. B. Harish Srinivasan, Sargur N Srihari. (2001) Cedar signature dataset. [Online]. Available: https://paperswithcode.com/dataset/cedar-signature

[6] R. Reni. (2023) Signature verification dataset. [Online]. Available: https://www.kaggle.com/datasets/robinreni/signature-verification-dataset