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Web-based Timber Logs Information System Using the YOLOv8 Model: IstifTakip

YOLOv8 Modeli ile Web Tabanlı Tomruk Bilgi Sistemi: İstifTakip

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Abstract

This study introduces İstifTakip, a web-based information system developed for the automated detection and measurement of stacked timber logs using the YOLOv8 deep learning model. The system aims to overcome the limitations of manual timber measurement methods by providing a more accurate and efficient alternative. Data were collected through smartphone images of timber stacks at the Ulucak Forest Depot in İzmir, Türkiye. The YOLOv8 model, optimized using the Optuna library, was trained on this dataset to detect logs and calculate key attributes such as diameter and volume. Hyperparameter optimization with Optuna resulted in a significant improvement in model performance, achieving an mAP@0.5 score of 0.8569, precision of 0.8513, and recall of 0.8827. These results demonstrate the model's robustness and accuracy in detecting logs across varied image conditions. İstifTakip was developed using the Django framework and offers a user-friendly interface where users can upload images, annotate reference lines, and obtain log measurements. The system is specifically designed for Turkish forestry, supporting local language and practices, which sets it apart from other global solutions. Its scalability and potential for integration with mobile devices make it a valuable tool for future forestry applications. This research highlights the advantages of combining deep learning and smart forestry technologies to enhance operational efficiency and data accuracy in timber stack management.

Keywords: Deep learning, Smart forestry, Timber detection, YOLOv8.

Özet

Bu çalışma, YOLOv8 derin öğrenme modeli kullanarak istiflenmiş tomrukların otomatik tespit ve ölçümünü sağlayan web tabanlı bir sistem olan İstifTakip'i tanıtmaktadır. Sistem, manuel tomruk ölçüm yöntemlerinin sınırlamalarını aşarak daha doğru ve verimli bir çözüm sunmayı hedeflemektedir. Veriler, Türkiye'nin İzmir ilindeki Ulucak Orman Deposu'nda tomruk istiflerinin akıllı telefonla çekilen görüntülerinden toplanmıştır. Bu görüntülerle çap ve hacim gibi özellikleri hesaplamak amacıyla YOLOv8 modeli Optuna kütüphanesi ile optimize edilmiştir. Optuna ile yapılan hiperparametre optimizasyonu, model performansını artırarak mAP@0.5 skoru 0.8569, doğruluk 0.8513 ve geri çağırma 0.8827 seviyelerine ulaşmıştır. Bu sonuçlar, modelin değişen görüntü koşullarında sağlam ve başarılı olduğunu göstermektedir. Django framework kullanılarak geliştirilen İstifTakip, kullanıcı dostu bir arayüze sahiptir. Kullanıcılar, bu arayüzde görüntü yükleyebilir, referans çizgileri ekleyebilir ve tomruk ölçümleri alabilir. Türk ormancılığına özel olarak tasarlanan sistem, yerel dil desteği ve uygulamalarıyla öne çıkmakta olup, küresel çözümlerden ayrılmaktadır. Ayrıca, mobil cihazlarla entegrasyon potansiyeli ve ölçeklenebilirliği ile gelecekteki ormancılık uygulamaları için değerli bir araç niteliğindedir. Bu araştırma, derin öğrenme ve akıllı ormancılık teknolojilerinin bir araya gelerek istif yönetiminde operasyonel verimlilik ve veri doğruluğunu artırmadaki avantajlarını vurgulamaktadır.

Anahtar Kelimeler: Derin öğrenme, Akıllı ormancılık, Tomruk tespit, YOLOv8.

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1. Introduction

Forests are vital ecosystems that support human life by providing essential resources and ensuring environmental sustainability (Köse et al., 2017). Beyond their ecological significance, forest activities play a critical economic role, as highlighted by Gül and Özçelik (2017). Historically, forests have been predominantly seen as sources of timber. However, from the early 19th century onward, it became evident that forests serve multiple functions, including biodiversity conservation and climate regulation (Yıldırım, 2017; Vatandaşlar, 2021). Despite these diverse roles, the economic function of forests, particularly timber production, remains the primary focus today.

One of the key aspects of timber production is the efficient management of timber resources from forest extraction to storage and distribution. Timber stacking, drying, protection, and transportation are integral steps in ensuring sustainable forest management (Buğday and Özden, 2015). In Turkiye, timber delivered to forest depots is recorded manually, classified based on physical attributes such as type and quality, and measured for quantity, length, and diameter (Ünver Okan and Acar, 2015). This process, however, remains largely reliant on traditional methods, which poses challenges in terms of efficiency, accuracy, and scalability.

With the advancement of technology and the rise of digital solutions, there is an increasing need for the automation and digitization of these processes. Recent studies have explored the use of photogrammetry and remote sensing technologies such as UAVs (Unmanned Aerial Vehicles), smartphones, and LIDAR to capture and analyze timber data (Dietz et al., 2019; Karha et al., 2019; Eker and Aydın, 2020; Berendt et al., 2021; Uçar et al., 2024; Sönmez et al., 2024). These technologies offer promising solutions for accurate and real-time data collection, which is essential for efficient forest management.

As timber is both a capital asset and a revenue source for forest enterprises, the accurate, fast, and cost-effective measurement of logs is crucial for operational success (Türker, 2013). The growing use of big data analytics in forestry provides an opportunity to collect and process large volumes of data for decision-making purposes. However, traditional methods of data collection and analysis are insufficient to meet the current demands for speed and precision (Zou et al., 2019). Therefore, the integration of big data and smart forestry technologies offers a potential solution to these challenges.

Smart forestry refers to the digital transformation and automation of forestry processes, leveraging Information and Communication Technologies (ICT) within the Industry 4.0

framework (Tomaszewski and Koakowski, 2023). This approach enables the digital, interconnected, and intelligent management of forest ecosystems, where data analysis and mining play a fundamental role in decision-making processes (Zou et al., 2019). One of the most pressing issues in the forestry sector is the accurate measurement, calculation, and documentation of stacked logs, which are critical for both economic and operational reasons.

To address this, various software and mobile applications have been developed, incorporating technologies such as computer vision and artificial neural networks for the precise measurement of log volumes. Among the most notable applications are Digitora (Bertola et al., 2003), NeuroDIC (Silveira et al., 2014), Trestima Stack (Karha et al., 2019), IFOVEA, LogStackPro, AFoRS, Logsize, sScale, and Timbeter (Uçar et al., 2024). These tools offer significant advantages, particularly for large-scale log stacks, by improving accuracy and reducing the time and costs associated with traditional measurement methods.

However, there is a limited body of literature focusing on the use of deep learning models such as YOLO (You Only Look Once) for log detection and measurement. Cassas et al. (2023) recently applied the YOLOv8 model to automatically detect eucalyptus logs, demonstrating the potential of this approach for real-time object detection in forestry applications.

In this study, we aim to contribute to the growing body of research by developing a practical and efficient solution for the automatic detection and measurement of timber log products. Using photogrammetric data, we calculate the number, diameter, and volume of stacked logs. The YOLO deep learning model, combined with the Optuna library for hyperparameter optimization, is employed to achieve accurate log detection from digital images. Upon completing accuracy tests, a web-based application called İstifTakip was developed to facilitate the practical use of this system in forest management.

2. Material and Method

2.1. Data Collection and Processing

The dataset for training and testing the deep learning model was created by capturing images of the existing timber stacks at the Ulucak Forest Depot, part of the İzmir Forest Regional Directorate, in 2024 (Figure 1). The data collection was carried out using two smartphones: an iPhone 14 Pro Max (48 MP) and a Samsung A02 (13 MP). A total of 262 images (.heic format) were captured with the iPhone, and 89 images (.jpeg format) were captured with the Samsung A02. Utilizing two devices facilitated faster data acquisition in the field while also allowing for an evaluation of the model's ability to generalize across different image qualities and resolutions. To ensure compatibility with the YOLO model, all images were converted to the .png format using the Python programming language (Figure 2).

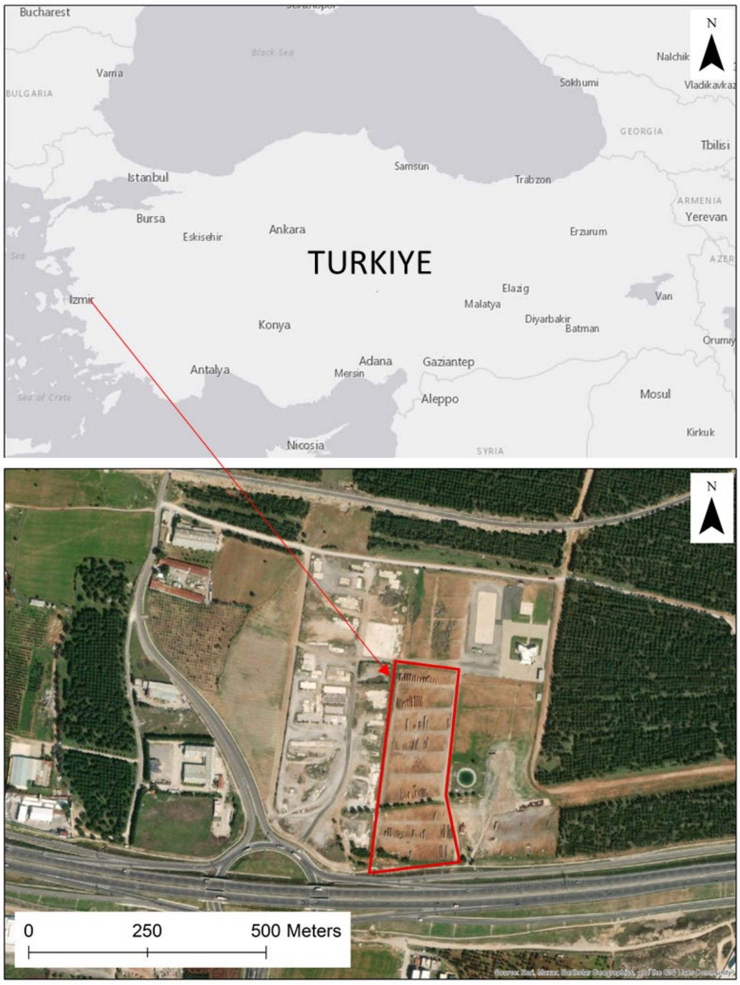

Figure 1. Location of the Ulucak Forest Depot where the images were captured.

Figure 2. Example images from the dataset of stacked timber logs.

The labeling of the timber logs in the images was carried out using the open-source software LabelImg (Figure 3). This software, with its graphical user interface (GUI), enabled accurate and efficient annotation of the timber log objects, saving the labels in the YOLO format.

Figure 3. The GUI of the LabelImg software used for image labeling.

2.2. YOLOv8 Model and Architecture

In this study, the YOLOv8 deep learning model was employed to automatically detect timber logs in the collected digital images. The backbone of the model was built using CSPDarknet53, an advanced version of the Darknet architecture known for its efficiency in object detection tasks. CSPDarknet53, as described in Casas et al. (2023), was chosen for its ability to handle complex and irregular object shapes, making it particularly well-suited for detecting stacked timber logs. The CSP (Cross Stage Partial Networks) approach used in this architecture allowed for partitioning the feature map, thereby reducing computational costs while maintaining high accuracy. This approach enhances gradient flow across layers, improving model performance. To further improve feature extraction, the C2f module (CSP Bottleneck with 2 Convolutions) was incorporated. This module allows the reuse of features across layers, enhancing the model's ability to detect logs of varying sizes and orientations. Additionally, the SPPF (Spatial Pyramid Pooling Fast) layer was used to manage varying spatial dimensions, making it easier for the model to detect objects at different scales and resolutions. These improvements in the architecture align with the enhancements proposed by Casas et al. (2023) for optimizing object detection tasks. The model was trained using the AdamW optimizer, which provides a balance between speed and accuracy through decoupled weight decay regularization. This regularization prevents overfitting during training, improving the model's generalization to unseen data.

2.3. Hyperparameter Optimization with Optuna

Unlike the approach taken by Casas et al. (2023), to ensure the best model performance, hyperparameter optimization was carried out using the Optuna library. The following key hyperparameters were optimized: the number of epochs, batch size, learning rate, momentum, and weight decay (see Table 1). Optuna conducted 10 trials of optimization to identify the optimal combination of these parameters. The final model was selected based on the highest mAP@0.5 (mean Average Precision at 50% Intersection over Union) score, which evaluates the model’s detection accuracy.

Table 1. Summary of basic parameters optimized during the training process using the Optuna library.

Parameter	Range/Value	Description
Epochs	Between 50-100	Number of complete passes through the training dataset.
Batch size	8, 16, 32	Number of samples processed before the model is updated.
Learning rate	Between 1e-5 and 1e-1 (log scale)	Step size controlling how much to adjust the weights.
Momentum	0.5 - 0.99	Helps accelerate gradient vectors in the right direction.
Weight decay	Between 1e-6 and 1e-3	Regularization technique to prevent overfitting.
Number of Trials	10	Number of trials conducted for hyperparameter tuning.
Performance Metric	mAP@0.5	Mean Average Precision at 0.5 IoU used to select the best model.

2.4. Model Evaluation and Deployment

The model evaluation process was conducted in two main stages: validation during training and testing on an independent test set. The dataset was divided into training and testing sets based on the device used to capture the images. Images captured with the iPhone 14 Pro Max were used for training the model, while those captured with the Samsung A02 were used exclusively for testing purposes. During the training process, the model's performance was continuously evaluated using a validation split from the training data. The following evaluation metrics were employed to measure the model's performance:

- *Precision:* Precision is the ratio of true positive detections to the sum of true positives and false positives. It represents the accuracy of the model in identifying timber logs without falsely detecting non-log objects. High precision indicates that the model effectively minimizes false positives.

- *Recall:* Recall is the ratio of true positive detections to the sum of true positives and false negatives. It measures the ability of the model to correctly identify all the actual timber logs in the image. High recall indicates that the model successfully detects most, if not all, of the logs.

- *mAP@0.5 (Mean Average Precision at 50% IoU):* This metric is used to evaluate the overall detection performance of the model. The mean average precision (mAP) is calculated by taking the average of the precision values at different recall levels, while the 0.5 Intersection over Union (IoU) threshold is used to determine whether a predicted bounding box overlaps sufficiently with the ground truth box. A higher mAP@0.5 score reflects better accuracy in detecting the logs with precise bounding box placement.

mAP@0.5 is widely used in object detection tasks because it provides a comprehensive evaluation of how well a model can detect and localize objects. A high mAP@0.5 score indicates that the model can accurately detect objects with a reasonably high overlap between predicted and ground truth boxes. It balances precision and recall, making it a reliable metric for evaluating object detection performance. The model was then integrated into the IstifTakip Web-based Information System.

2.5. Designing of IstifTakip Web-based Information System

The design of the IstifTakip web-based system involved a structured approach that combined deep learning integration, user interface design, and backend architecture to deliver an efficient and user-friendly solution for detecting and managing timber logs. The workflow diagram is given in Figure 4.

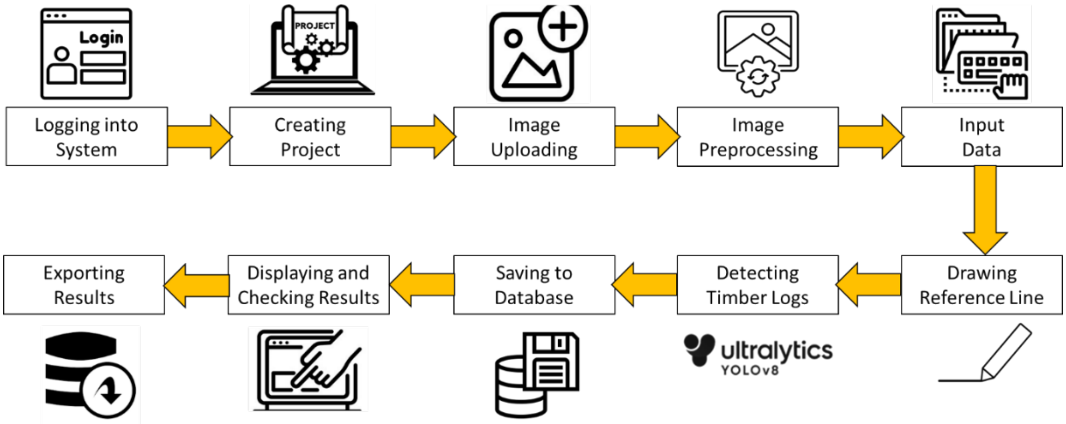

Figure 4. Workflow diagram of IstifTakip Web Application.

According to this diagram, below is a step-by-step explanation of how the IstifTakip system works:

- *Logging into the System:* The process begins when the user logs into the web application. This secure login step ensures that only authorized users can access and manage the timber log detection process.
- *Creating a New Project:* Once logged in, the user can create a new project. Users can define name for the Project by entering additional explanations.
- *Image Uploading:* After the project is set up, users upload images of stacked timber logs. The system supports various image formats
- *Image Preprocessing:* Before the images are analyzed, they undergo preprocessing that involves resizing and ensuring that the images are in a format suitable for the YOLOv8 model.
- *Input Data:* Any additional information about the timber stack (e.g., tree species, log length, stack id, etc.)
- *Drawing Reference Line:* To scale estimated diameters of each log detected, a reference line is drawn on the image.
- *Detecting Timber Logs:* The core of the system is the YOLOv8 model, which processes the preprocessed images and detects the timber logs.

• *Displaying and Checking Results:* The results of the detection are displayed in an intuitive and interactive web interface. Users can view the images with the detected logs, along with key metrics such as log count, diameters, and volume.

• *Exporting Results:* Finally, the detected log data can be exported in various formats such as excel and pdf files.

The developing algorithms were carried out based on the workflow diagram given. The development process relied on the Django framework, which adheres to the Model-View-Controller (MVC) design pattern. This design pattern ensured a clear separation of concerns, promoting both scalability and maintainability throughout the application. In the system, the models define the database schema, which represents the core attributes of timber logs, such as size, species, and volume. These models are crucial for structuring and organizing the data, enabling efficient storage and retrieval. The views, on the other hand, manage user interactions, such as image uploads for log detection and displaying the results. They act as the intermediary between the front-end interface and the backend logic, ensuring a seamless user experience. Django's URL routing system serves as the controller, directing user requests to the appropriate views and managing data flow throughout the application.

At the core of the system is the YOLOv8 deep learning model, which is responsible for detecting and classifying timber logs in images. The model was deployed on the server-side, allowing for real-time image processing. When users upload images, the system passes these through the YOLOv8 model, which identifies the logs, draws bounding boxes around them, and calculates essential properties such as log volume. To ensure smooth operation, the system preprocesses all images, resizing and normalizing them to meet the input requirements of the YOLO model. This preprocessing step ensures that the model functions optimally, regardless of the type or size of the input images.

The front-end of the IstifTakip application was designed with user experience in mind, especially targeting forestry professionals who may not have extensive technical knowledge. The interface, built using HTML, CSS, and JavaScript, offers a simple yet effective layout where users can easily upload images of timber stacks. The upload process is optimized for handling large files efficiently. Once the YOLO model processes an image, the detected logs are highlighted, and relevant data, such as log diameter, length, and volume, are displayed to the user in an interactive manner. This interactive interface allows users to zoom in on the logs and examine the detection results in detail.

On the backend, Django's Object-Relational Mapping (ORM) handles data management. PostgreSQL was chosen as the database system to manage large datasets, ensuring quick retrieval and scalable storage. The ORM simplifies database interactions, enabling the system to grow and adapt as more data is collected or additional features are added. The system also includes a secure user authentication mechanism, allowing forestry professionals to create accounts, upload images, and access detection results. Role-based access control ensures that different users have appropriate permissions, allowing only authorized personnel to manage or modify log data.

3. Results and Discussion

In this study, we aimed to evaluate the performance of the YOLOv8 model in detecting and analyzing stacked timber logs using the İstifTakip web-based system. We implemented a hyperparameter optimization process using the Optuna library to fine-tune the model, assessing key performance metrics such as mAP50, Precision, and Recall. Through rigorous testing on images from different devices, the results demonstrated significant accuracy and robustness, supporting the potential of this deep learning system in forestry applications.

3.1. Results

3.1.1. Model Performance and Optuna Hyperparameter Optimization

During the Optuna optimization process, 10 trials were conducted to fine-tune the YOLOv8 model for the task of timber log detection. The metrics of interest, including mAP50, mAP50-95, Precision, and Recall, were evaluated for each trial (Figure 5-Figure 8). The results varied across the trials, as summarized in the following key findings:

• *mAP50:* This metric, representing the model's ability to detect timber logs with 50% Intersection over Union (IoU), ranged between 0.8454 and 0.8569 across the trials. Trial 5 showed the highest mAP50 score of 0.8569, making it the most effective in detecting timber logs with a high degree of overlap between predicted and actual bounding boxes.

• *mAP50-95:* The model's performance at different IoU thresholds (from 50% to 95%) also indicated the robustness of the detection. The mAP50-95 values ranged from 0.6669 to 0.6956, with Trial 5 again showing the best performance at 0.6956.

• *Precision:* The highest precision was observed in Trial 4 with a perfect score of 1.000, meaning no false positives were detected in that trial. However, Trial 5 achieved a balanced precision score of 0.8513, ensuring the model could detect logs without significant over-detection (false positives).

• *Recall:* Recall, which measures the model's ability to detect all relevant logs, ranged between 0.8471 and 0.8940. Trial 2 demonstrated the highest recall value of 0.8940, while Trial 5 maintained a strong recall score of 0.8827, indicating that the model successfully detected most logs in the images.

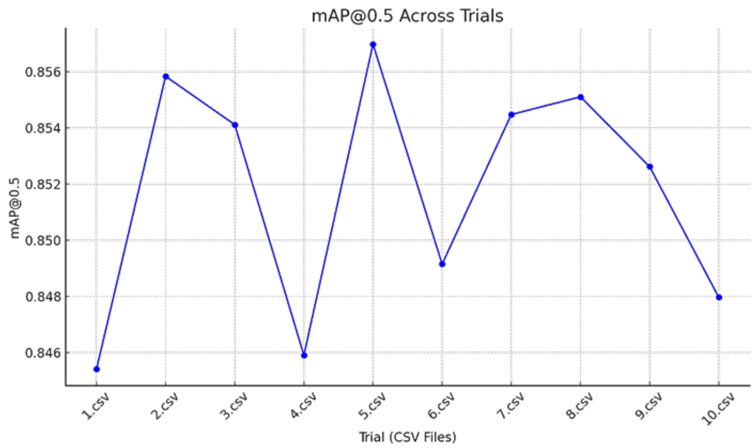

Figure 5. mAP@0.5 Across Trials.

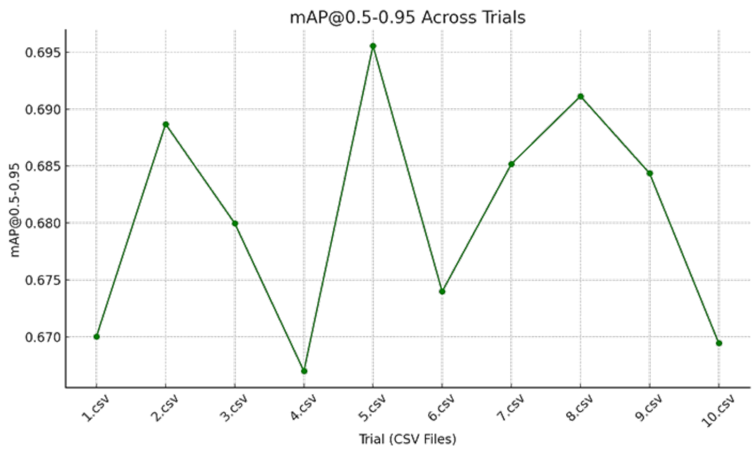

Figure 6. mAP@0.5-0.95 Across Trials.

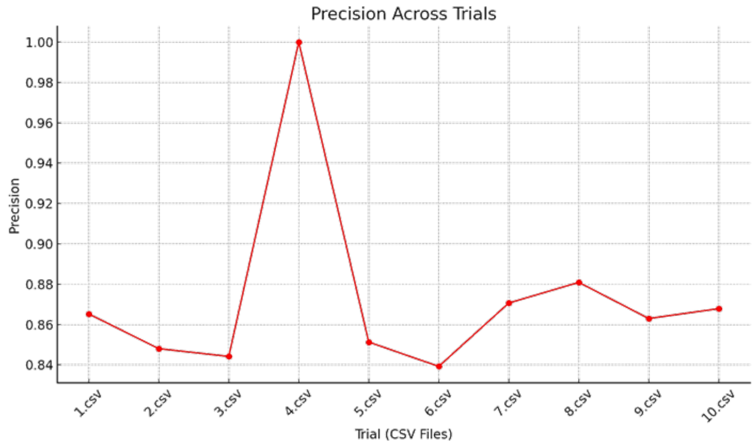

Figure 7. Precision Across Trials.

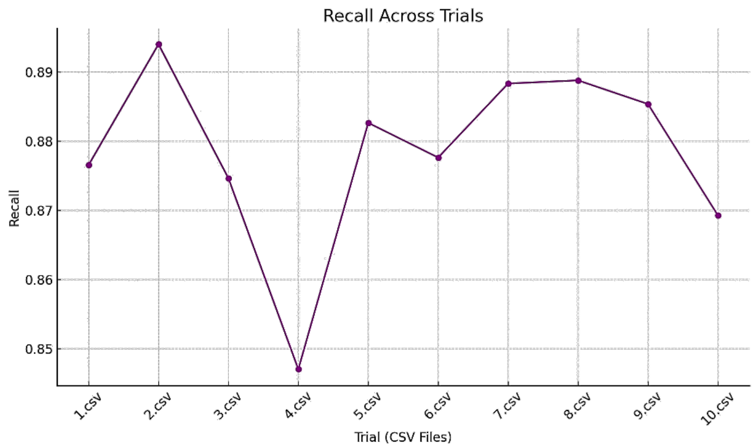

Figure 8. Recall Across Trials.

Based on the overall performance metrics, Trial 5 was identified as the best-performing model, balancing both precision and recall while achieving the highest mAP scores. The model performance in Trial 5 was further assessed by analyzing the training and validation loss curves, as well as key evaluation metrics such as precision, recall, and mAP (Mean Average Precision) (Figure 9). The following observations were made from the provided graphs:

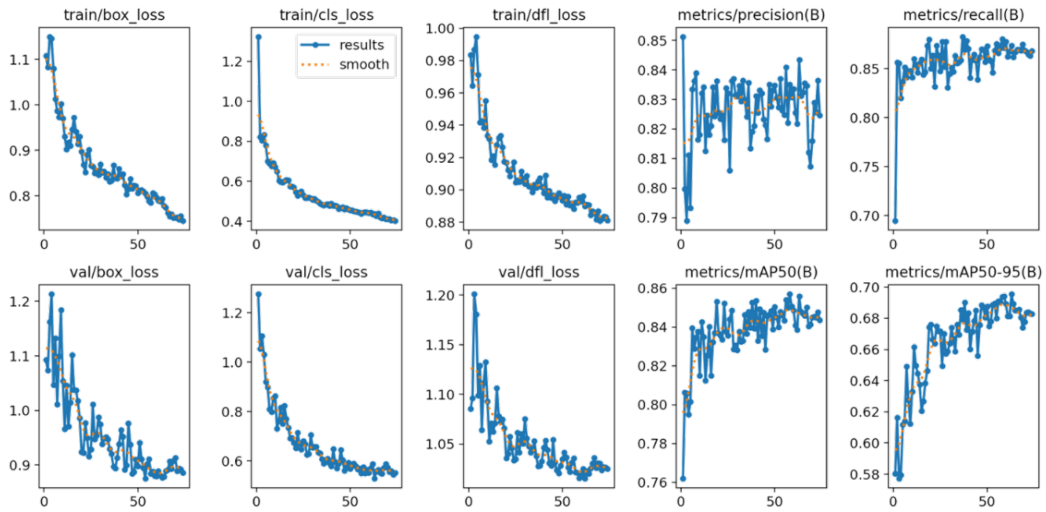

Figure 9. The model performance graphs in Trial 5.

• *Training Losses:* The train/box_loss, train/cls_loss, and train/dfl_loss curves (top row, first three plots) consistently decrease as the number of epochs increases, indicating that the model is learning effectively and minimizing errors related to bounding box localization, classification, and distributional loss functions, respectively.

• *Validation Losses:* The validation losses (val/box_loss, val/cls_loss, val/dfl_loss), shown in the bottom row, also demonstrate a steady reduction across epochs, mirroring the training losses. This suggests that the model generalizes well to unseen validation data and does not suffer from significant overfitting.

• *Precision and Recall:* The precision (top row, fourth plot) shows minor fluctuations but stabilizes after several epochs, reaching a final value of approximately 0.85. Similarly, the recall (top row, fifth plot) increases steadily throughout training, stabilizing around 0.88.

• *mAP50 and mAP50-95:* The mAP50 and mAP50-95 curves (bottom row, last two plots) show steady improvement, with the mAP50 metric nearing 0.86 and mAP50-95 stabilizing around 0.69. These metrics further confirm the robustness of the model in detecting timber logs with high precision and accuracy.

To further evaluate the performance of the model selected in Trial 5, several key confidence metrics were examined. These curves provide valuable insights into how the model's precision, recall, and F1 score change as a function of the confidence threshold (Figure 10).

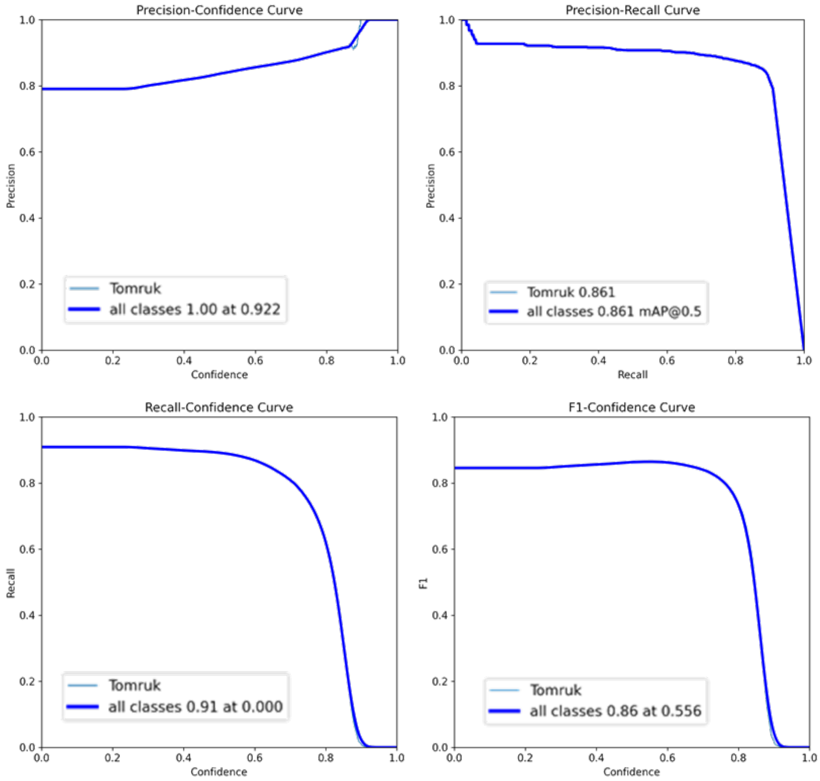

Figure 10. The several key confidence metrics were examined model performance graphs in Trial 5.

• *Precision-Confidence Curve (Top Left):* The precision remains high and stable above 0.95 for confidence thresholds between 0.5 and 0.9, indicating that the model maintains high accuracy in predicting timber logs at a variety of confidence levels. This stability suggests that the model is not overfitting and is reliable in practical applications where high-confidence predictions are required.

• *Precision-Recall Curve (Top Right):* The Precision-Recall curve shows that the model achieves a balance between these two metrics, stabilizing at a high recall while maintaining strong precision. The drop in precision at lower recall values is expected in models with high precision but reflects that most detected logs are relevant, even if some logs remain undetected at lower thresholds.

• *Recall-Confidence Curve (Bottom Left):* The recall remains stable at high confidence thresholds, ensuring that the model captures a significant portion of true positives while maintaining robustness in real-world conditions. The sharp drop-off after 0.9 confidence indicates that, at extremely high thresholds, the model becomes more conservative in its detections.

• *F1-Confidence Curve (Bottom Right):* The F1 score, which balances precision and recall, peaks around 0.6 confidence and remains relatively stable, suggesting that this confidence level is the optimal trade-off point for both metrics.

The model exhibits strong stability across various confidence levels, and the F1-Confidence curve provides a clear indication of the optimal confidence threshold for deployment in forestry applications. The precision and recall trade-off, as seen in the Precision-Recall curve, further validates the effectiveness of the model in detecting timber logs with minimal false positives, making it ideal for the İstifTakip web system. Based on all these results given above, his model was selected for integration into the İstifTakip web-based system. Its ability to generalize well across the dataset, with consistently high mAP, precision, and recall, made it ideal for the practical detection of stacked timber logs in a variety of real-world forestry conditions.

3.1.2. IstifTakip Web Application

The user interface and related pages developed for the IstifTakip web application are presented here as findings. The application has not yet been made available online. However, when the application is launched, the first screen that appears allows users to either create an account or log in (Figure 11). This page also provides information about the IstifTakip web application. Currently, the application is available only in Turkish, but it will be accessible in other languages once the development process is completed. To create an account, users need to fill out a form, and after their account is approved by the admin, they can log in and start using the application. The login page is shown in Figure 12.

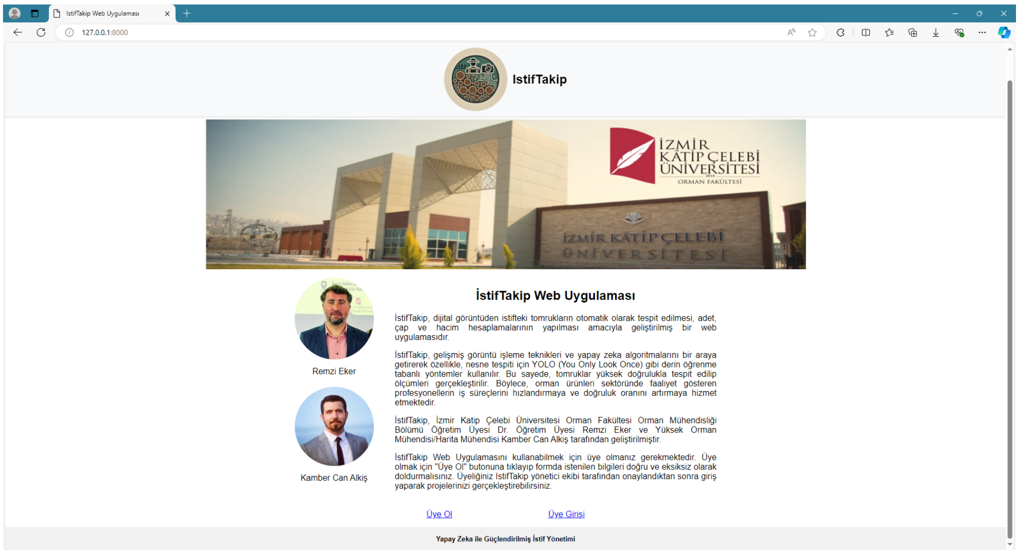

Figure 11. Login and registration page of the IstifTakip web application.

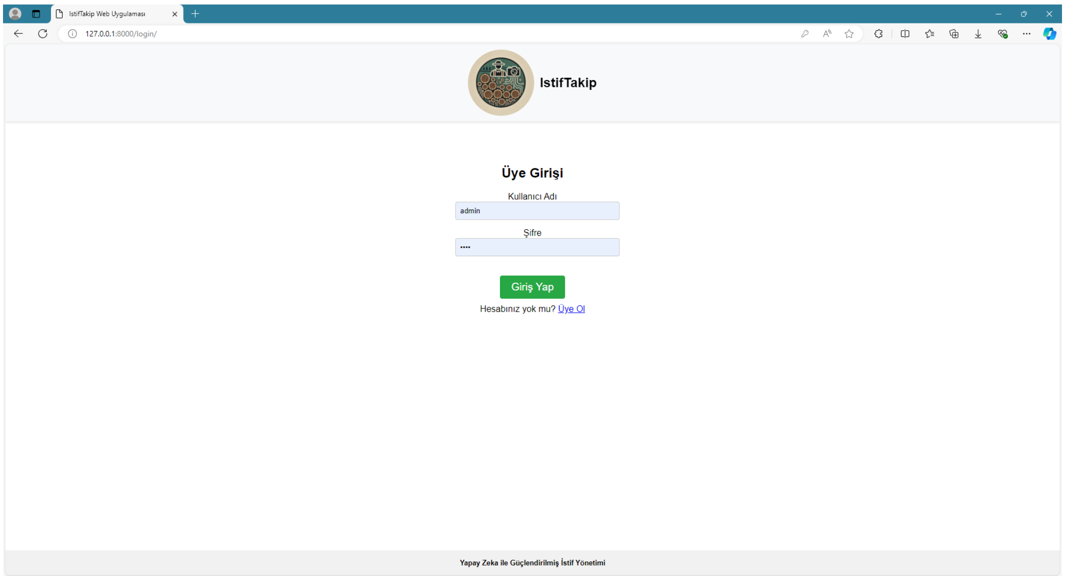

Figure 12. User login page.

Once the user has logged in, they can access the profile page and start a project (Figure 13). This page also allows the user to log out of the application.

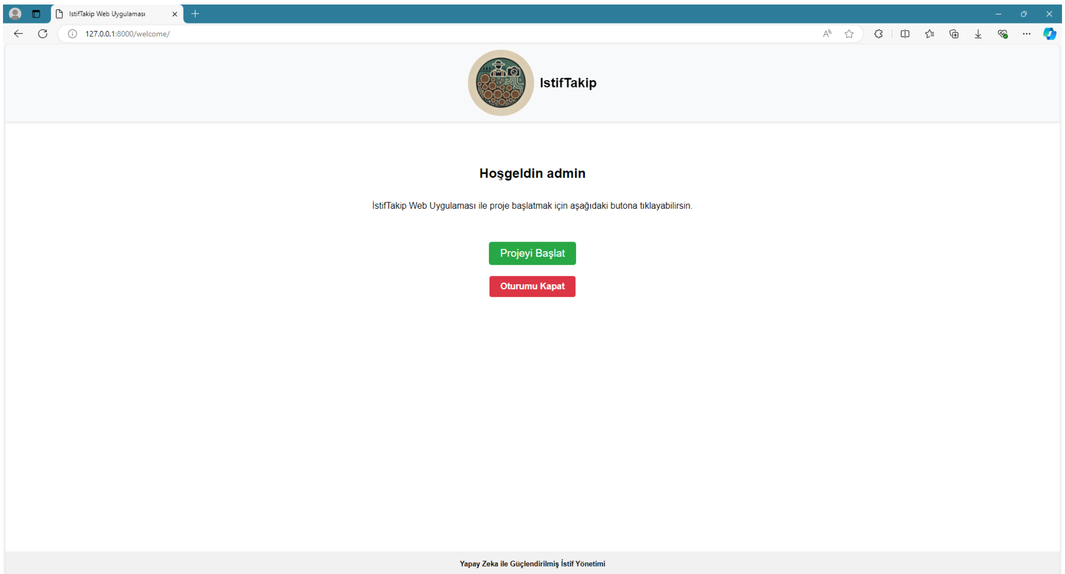

Figure 13. Profile page where users can start a new project or log out.

After the user starts a project, they are directed to the project creation screen (Figure 14). This page includes text fields for the project name and description. After entering the necessary information, the user is redirected to a page where they can select an image for the project (Figure 15). The selected image is then uploaded to the server for further processing.

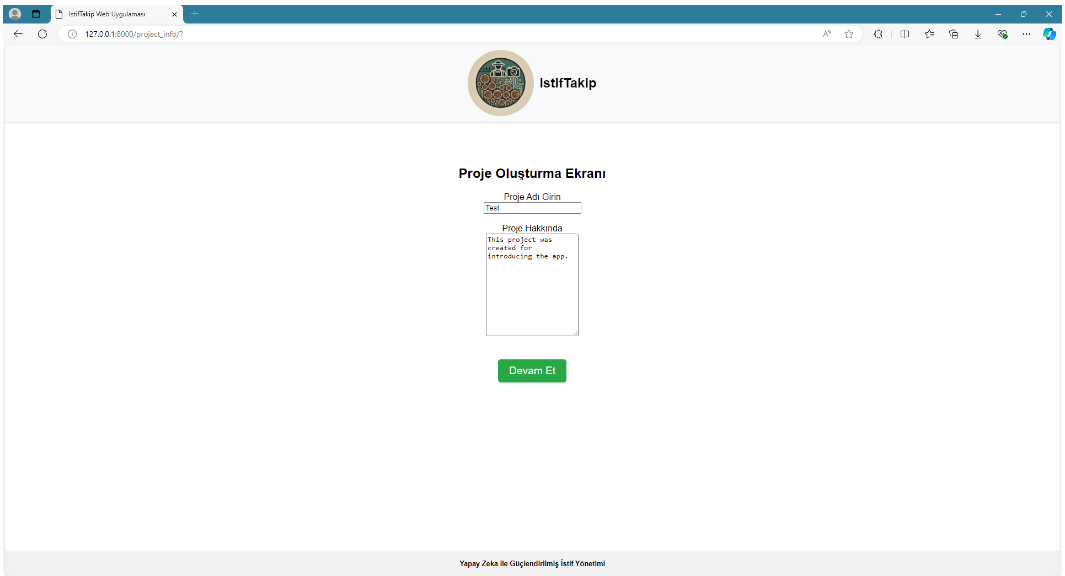

Figure 14. Project creation page with fields for project name and description.

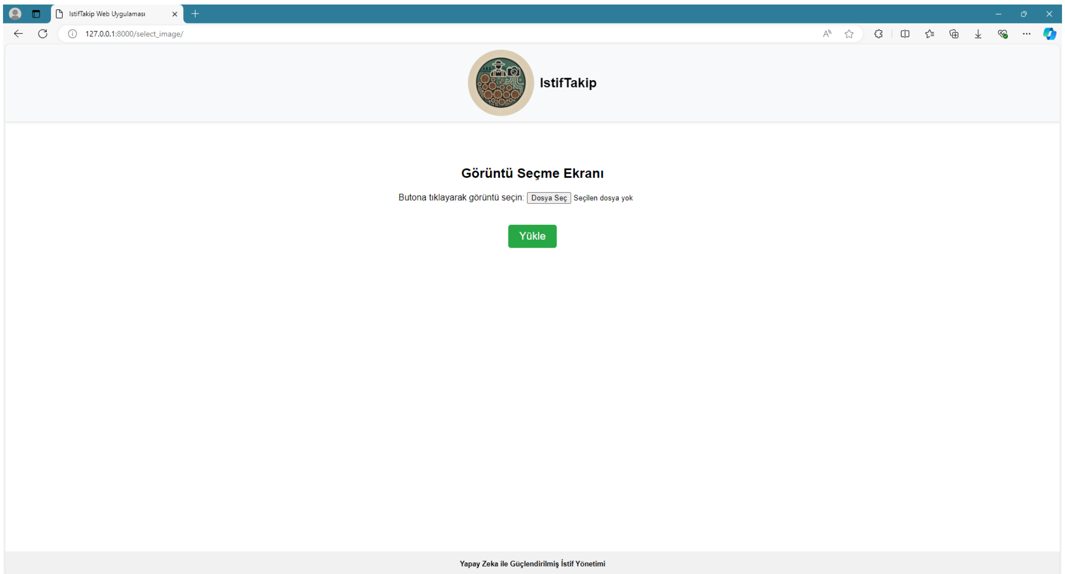

Figure 15. Image selection page for project setup.

After selecting an image, the user is required to input details about the stack, such as tree species, log length, and stack number. This is done on the page shown in Figure 16. In the next step, the user moves to the page where they can draw a reference line (Figure 17). On this page, the user draws on the selected image using the mouse. Once the reference line is drawn, it is confirmed, and the length is entered in centimeters.

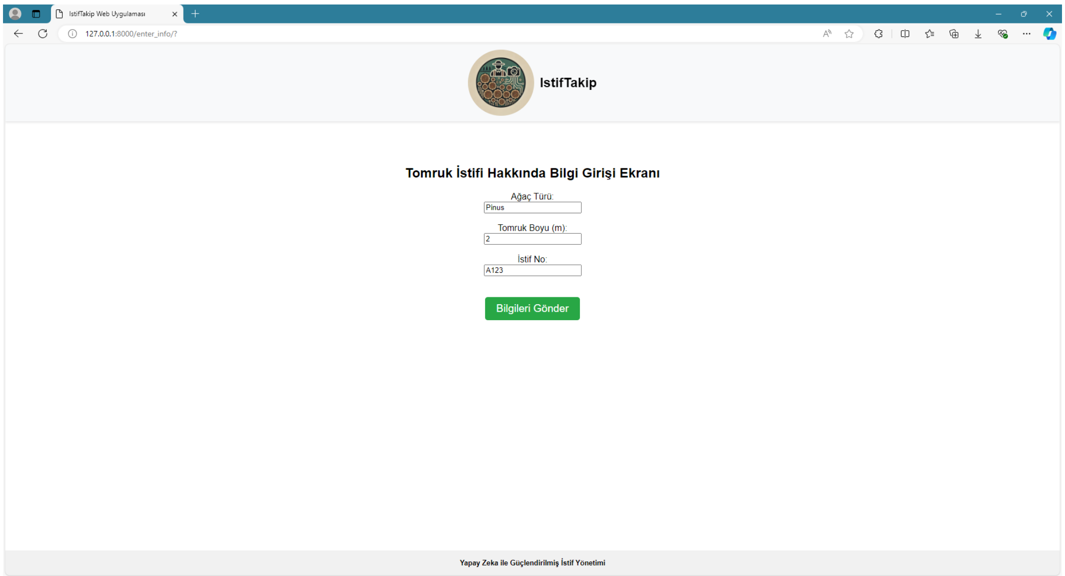

Figure 16. Page for entering log details, including tree species, log length, and stack number.

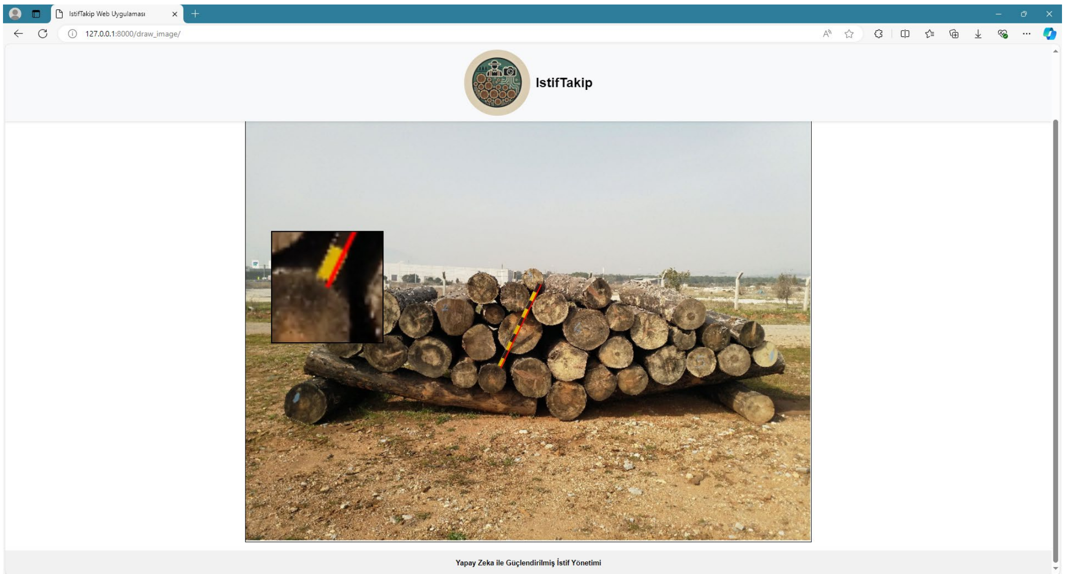

Figure 17. Reference line drawing page with a canvas for user input.

After the reference line length is provided, the next page shows the detected logs, marked with circles, along with diameter information (Figure 18). During the transition from the reference line drawing page, the application uses a YOLOv8-based model to detect the logs in the background. The image quality, resolution, and brightness play a significant role in accurately detecting the logs. If the model fails to detect some logs or the circles drawn by the application are inaccurate, the user can manually adjust them. This includes deleting, resizing, moving, or adding new circles using the mouse. A pop-up window appears when the page first opens to inform the user about the circle editing process. The user must visually verify that the logs in the stack are correctly detected and that the circles are drawn in the correct positions and sizes. Once confirmed, the user can obtain the number, diameter, volume values, and descriptive statistics of the logs in the stack (Figure 19). The user can then download the stack outputs as MS Office Excel or PDF files. Additionally, the user can select new images for other stacks within the project and repeat the same steps to generate reports.

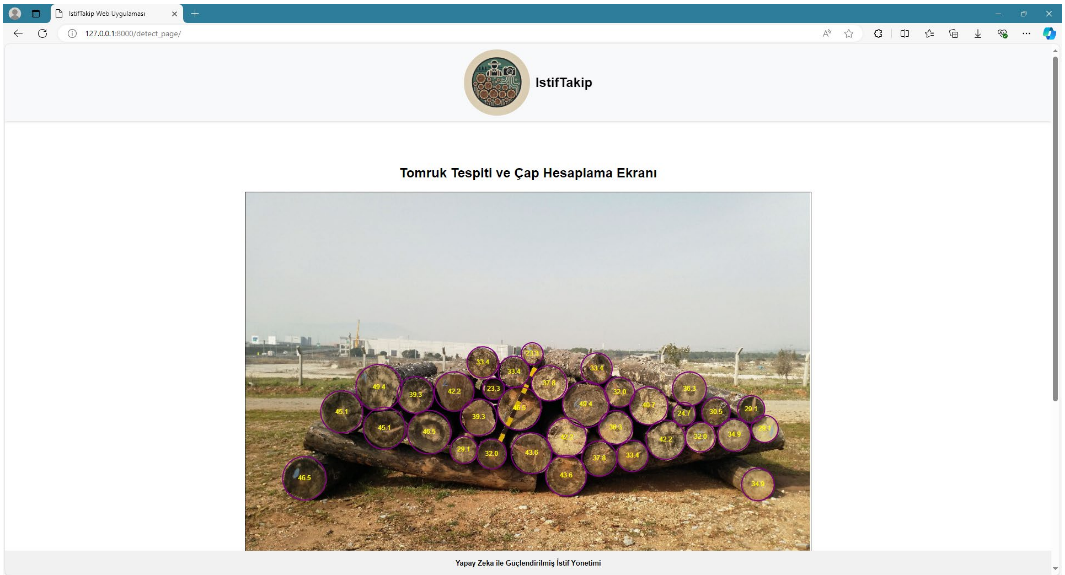

Figure 18. Page showing detected logs with circles and diameter information.

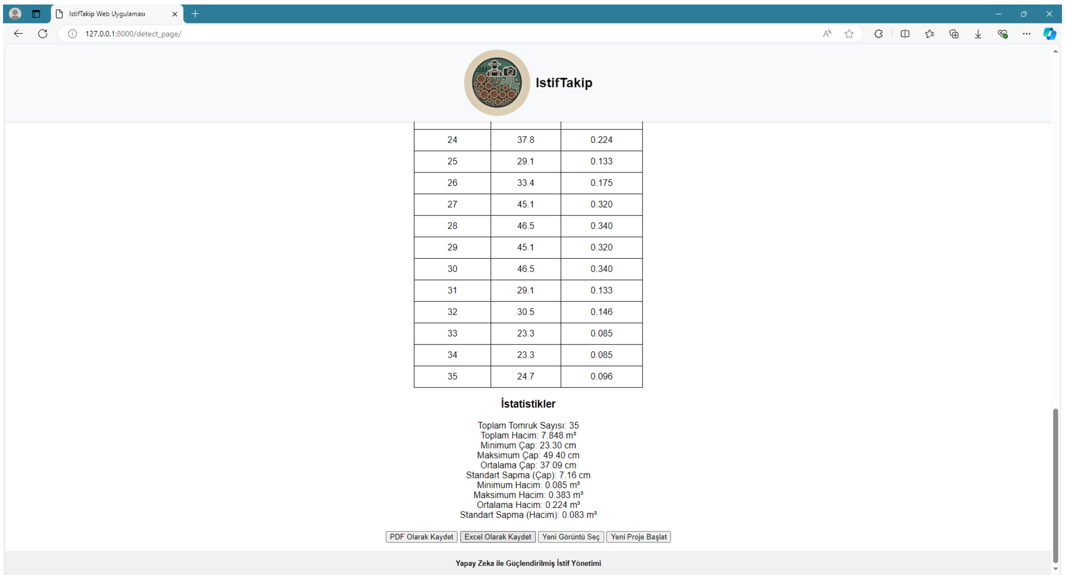

Figure 19. Final report page with the number of logs, diameter, volume statistics, and export options.

3.2. Discussion

In this study, the İstifTakip system, which integrates the YOLOv8 deep learning model, was developed and tested for the detection and measurement of stacked timber logs. The system performed well in terms of precision, recall, and overall detection accuracy, demonstrating its potential for application in real-world forestry operations. One of the key strengths of this study is the integration of the Optuna library for hyperparameter optimization, which sets this work apart from others in the field and contributes significantly to the model's superior performance.

A major differentiator of this study is the use of Optuna for hyperparameter optimization, which allowed for fine-tuning critical model parameters such as learning rate, batch size, momentum, and weight decay. This approach enabled the system to achieve high mAP@0.5 scores, demonstrating its accuracy in detecting timber logs with precise bounding boxes. Compared to traditional methods of hyperparameter tuning, such as grid search or manual tuning, Optuna offers a more efficient and adaptive optimization process. This not only speeds up model training but also ensures better generalization across different datasets and conditions. As the forestry sector increasingly adopts digital technologies, the ability to optimize deep learning models efficiently will become even more critical.

The flexibility and efficiency of Optuna allow İstifTakip to adapt to diverse environments, handling varying log sizes, orientations, and stacking configurations. This adaptability is crucial in forestry applications, where environmental factors and image quality can significantly impact detection accuracy. While other studies, such as Casas et al. (2023), applied YOLOv8 without focusing on advanced optimization techniques, our use of Optuna enhances the model's robustness and performance, ensuring higher detection accuracy even in complex scenarios.

When comparing the results of this study with existing research, several key points emerge. Casas et al. (2023) applied the YOLOv8 model for detecting eucalyptus timber logs, achieving a precision of 0.778 and mAP@0.5 of 0.839. In our study, İstifTakip achieved comparable detection accuracy, though some challenges were noted in tightly packed log configurations. Similar to the findings of Casas et al., our system encountered difficulties in counting logs in densely stacked images. To address this, future iterations of İstifTakip could incorporate video-based detection, as suggested by Casas et al. (2023), which has been shown to significantly reduce counting errors by as much as 12.4%.

On the other hand, Tomczak et al. (2024) evaluated photo-optical measurement systems such as LogStackPro, iFovea, and Timbeter, which reported deviations of 3.37% to 9.08% compared to manual measurements. While this study did not perform a direct comparison between İstifTakip and manual methods, our results demonstrate similar accuracy levels, placing the system on par with these commercial solutions. The deep learning architecture of YOLOv8, optimized with Optuna, provides greater flexibility in handling irregularly shaped logs and non-uniform stacks, which are common in real-world scenarios. It is important to note that this study did not include a direct comparison between the İstifTakip system and manual timber measurement methods. Although manual measurements are often used as benchmarks in forestry applications, the focus of this study was on developing an automated system that could operate independently of manual processes. As such, the results should be interpreted with this limitation in mind. However, future research could explore how the system performs relative to manual methods, providing a more comprehensive evaluation of its accuracy and efficiency.

Additionally, Uçar et al. (2024) tested mobile applications such as iFovea Pro and Timbeter in Turkish forestry for measuring log volumes. While these applications were found to be effective, İstifTakip presents distinct advantages for Turkish forestry. One of the key benefits is that İstifTakip is designed with Turkish language support and interfaces directly with local forestry practices. This is particularly important because forestry professionals in Turkiye may benefit from using a system in their native language, which reduces the learning curve and enhances usability. Moreover, İstifTakip's web-based architecture makes it easy to update and expand, ensuring that it can be quickly adapted to the evolving needs of Turkish forestry. Uçar et al. (2024) also highlighted the potential of mobile applications like iFovea Pro and Timbeter for the Turkish market; however, these apps primarily cater to an international audience, and their user interfaces and functionalities may not fully align with the specific requirements of Turkish forestry operations. In contrast, İstifTakip, being specifically designed with the local market in mind, has the potential to integrate seamlessly with national forestry databases, regulations, and workflows. Its flexibility and openness to further development make it highly adaptable to future forestry needs in Turkiye.

Despite the strong performance of İstifTakip, particularly in image-based detection and volume estimation, there are areas where the system can be further improved. One challenge noted during the study was the difficulty in counting logs in tightly stacked configurations. This is a common issue in timber detection systems. Additionally, the scalability of the system is another key advantage. The İstifTakip system, with its web-based architecture and deep learning foundation, is well-suited for handling large datasets and providing real-time results. This scalability makes it ideal for large-scale forestry operations where processing speed and accuracy are critical. Moreover, although İstifTakip is currently a web-based application, there are plans for the development of mobile versions in the future. This would further expand its usability, enabling forestry professionals to access the system on-site, making data collection and log detection even more efficient. The introduction of mobile versions would allow for even greater flexibility in the field, where access to a desktop or laptop might not always be feasible. This future development is critical for ensuring that İstifTakip remains a comprehensive and adaptable solution for modern forestry management.

4. Conclusion

This study presents the development of İstifTakip, a web-based system that uses the YOLOv8 deep learning model to automatically detect and measure stacked timber logs. The system aims to overcome the limitations and inefficiencies of traditional manual measurement methods. The system is optimized through hyperparameter tuning using the Optuna library, which resulted in significant performance improvements, achieving an mAP@0.5 score of 0.8569, with precision and recall values of 0.8513 and 0.8827, respectively. These results highlight the system's robust capability to detect timber logs accurately in various image conditions, demonstrating its effectiveness in real-world forestry applications.

A key contribution of this research is the development of a system specifically designed for Turkish forestry operations. İstifTakip is currently available in Turkish, which provides a significant advantage for local users by reducing the learning curve and integrating smoothly into established workflows. Moreover, the system’s design allows for future scalability and adaptability, ensuring that it can meet the evolving needs of the forestry sector. Although the application is currently only available in Turkish, it will be adapted to other languages, starting with English, broadening its accessibility for international users and expanding its potential impact globally.

The use of Optuna for hyperparameter optimization sets this study apart from other timber detection solutions, enabling superior performance by fine-tuning key model parameters. İstifTakip demonstrates strong adaptability, handling variations in log size, orientation, and stacking configuration, which are common challenges in forestry operations.

However, challenges remain in detecting logs within tightly packed configurations, an area where future research and development could focus on enhancing algorithmic precision. Additionally, the planned development of a mobile version will further improve its field usability, enabling real-time timber detection and measurement in on-site forestry operations.

In conclusion, İstifTakip represents a significant advancement in smart forestry solutions, combining deep learning with practical forestry management tools to improve operational efficiency, accuracy, and data management. With its current success in the Turkish market and plans for international language support, İstifTakip holds great potential for transforming timber log management not only in Türkiye but also in broader forestry sectors globally.

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