Enhanced Aircraft Takeoff/Landing Safety using Deep Learning Model in Runway Assistance System

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Abstract

In this paper, we present the development of a novel obstacle detection method using a YOLO-LSTM-based system to enhance runway safety during takeoff and landing. The system uses four strategically positioned cameras to provide real-time, precise detection and tracking of the detected obstacles around the runway. The YOLO model is employed for its superior object detection capabilities and on the other hand LSTM model is used for its strength in sequence prediction, allowing for accurate prediction of obstacle trajectories. This integrated method enhances situational awareness and facilitates proactive risk avoidance, significantly improving safety during critical flight operations. Moreover, this study emphasizes the importance of building trust in runway control station operations through a thorough review and strategic application of data, optimizing decision-making processes, operational techniques, and overall control center efficiency. The proposed system seeks to mitigate risks and ensure safer aviation operations by reducing operator stress and enhancing service satisfaction. The comprehensive evaluation and strategic application of data underlines the potential of this advanced AI framework to revolutionize runway safety protocols.

Keywords: Detection, Prediction, Runway Control Assistant

1. Introduction

The runway control tower situated at the airfield serves as a critical hub positioned at the landing point of the runway, approximately 1200 to 1500 feet above ground level. Its essential responsibilities involve handling landing control, providing flight guidance, reacting to emergencies, and guaranteeing short-range aircraft safety. The current operating environment, which mostly depends on employees' talents for operational support and emergency guidance, is constrained by the lack of quantitative tools and processes. It is obvious that there are now operational constraints with the control station. These consist of things like the lack of monitoring systems for unexpected risks during the takeoff and landing phases, including bird collisions, and the unavailability of reliable flight information for control station workers. Unexpectedly, data indicates a high frequency of bird collisions, occurring during the crucial takeoff and landing phases over ten years.

To address these challenges and safety measures, this paper proposes the development of a comprehensive detection system that leverages advanced artificial intelligence techniques. Specifically, we integrated YOLO (You Only Look Once) and LSTM (Long Short-Term Memory) models within a deep learning framework to enhance runway safety by detecting and predicting obstacles around the runway using four strategically placed cameras. The YOLO model's superior object detection capabilities combined with the LSTM model's sequence prediction strengths enable real-time situational awareness and proactive risk mitigation.

This research uses strategic guidance from a Deep Learning-based system to improve safety procedures during the takeoff and landing phases. At the same time, it seeks to increase trust in runway control station operations by using gathered data and strategic analysis. Furthermore, the goal includes the implementation of a reduced one-person runway control station duty system, which departs from the existing team-based framework, in order to verify particular operational efficacy.

To enhance control station capabilities, cameras will be placed strategically at the ends of the runways, and an AI-based threat detection module will be developed. In order to identify and send information about possible dangers, such as drones and birds, to the control server in real-time, this module labels and trains threat object identification algorithms and prediction algorithms using virtual datasets as well as real-time video.

The research is expected to have a variety of effects that will improve aircraft operations. The main objective of implementing in place a thorough system is to greatly reduce operator stress, which is an essential part of their well-being and level of service satisfaction. Furthermore, by guaranteeing immediate and accurate guidance and reducing errors in crucial decision-making processes during emergencies, the system's integration is set to improve reactions to abnormal situations. This planned approach enhances safety precautions and gives employees more confidence to handle unexpected occurrences. The system's collected information has an impact that offers to expand its value across several operational and support domains within aviation, in addition to its immediate application in-flight safety. The planned gathering and examination of large-scale aircraft takeoff and landing data produces insights that go beyond safety measures, impacting operational plans, streamlining support services, and adding to a thorough knowledge of flight operations. The ultimate goal of this project is to bring about an evolution in aviation procedures by improving industry-wide decision-making, operational effectiveness, and safety standards.

1.1 Related Works

The application of deep learning for runway safety control systems for aircraft takeoff and landing has become a focal point of research and development within the aviation industry. Numerous studies and industry advancements have highlighted the potential of deep learning and artificial intelligence in elevating aviation safety and operational efficiency. One notable paper [1] endeavors to exploit the robustness of machine learning models to craft intelligent aviation safety systems. Additionally, ADB SAFEGATE's AiPRON 360 smart solution integrates AI, machine learning, and data analytics to effectively manage aircraft turnaround processes, contributing to heightened safety and efficiency [2]. Airbus has also conducted flight tests involving automatic takeoff and landing using computer vision and machine learning algorithms, demonstrating the considerable potential of these technologies in augmenting safety during critical phases of flight [3], [4]. The Journal of Big Data has featured research delving into the optimization of air traffic management efficiency through deep learning techniques, emphasizing their capability to evaluate safety factors during aircraft landing and takeoff [5]. Furthermore, a study in Communications Engineering has explored the creation of a multi-model architecture based on deep learning for aircraft load prediction, showcasing the versatility of deep learning across various flight phases, including takeoff and landing [6], [7], [8]. Collectively, these research papers underscore the potential of deep learning in fortifying runway safety control systems for aircraft takeoff and landing assistance. The integration of computer vision, machine learning, and data analytics stands as a promising avenue for enhancing safety and efficiency in aviation operations. Furthermore, the occurrence of runway slips or runway departures has attracted a lot of interest in the field of aviation safety because of the possible adverse outcomes. Runway slips are the result of an aircraft unintentionally drifting off the approved runway surface during taking off, or landing. In addition to frequently resulting in harm to the aircraft, infrastructure, and even casualties, these occurrences represent a major risk to passengers, crew, and observers.

This study introduces a comprehensive system with the primary goal of significantly alleviating operator stress, ensuring safety, enhancing service satisfaction, and mitigating risks in hazardous aviation situations. It underscores the critical need to instill trust in runway control station operations through meticulous data review and strategic application, optimizing decision-making processes, operational techniques, and overall control center efficiency.

2. Safety Runway Control Assistance

2.1 Proposed Framework

This paper proposes a novel YOLO-LSTM-based detection system to enhance runway safety during takeoff and landing by accurately identifying and predicting obstacles using a network of four strategically placed cameras. The system integrates the real-time object detection capabilities of YOLO with the sequence prediction strengths of LSTM, creating a comprehensive situational awareness tool. The key components of the framework include the camera network, the YOLO model for object detection, the LSTM model for trajectory prediction, a data processing unit, and a control server that provides a user interface for operators. Additionally, an alert and guidance system supports proactive risk mitigation by recommending adjustments to flight operations based on real-time data and predictions.

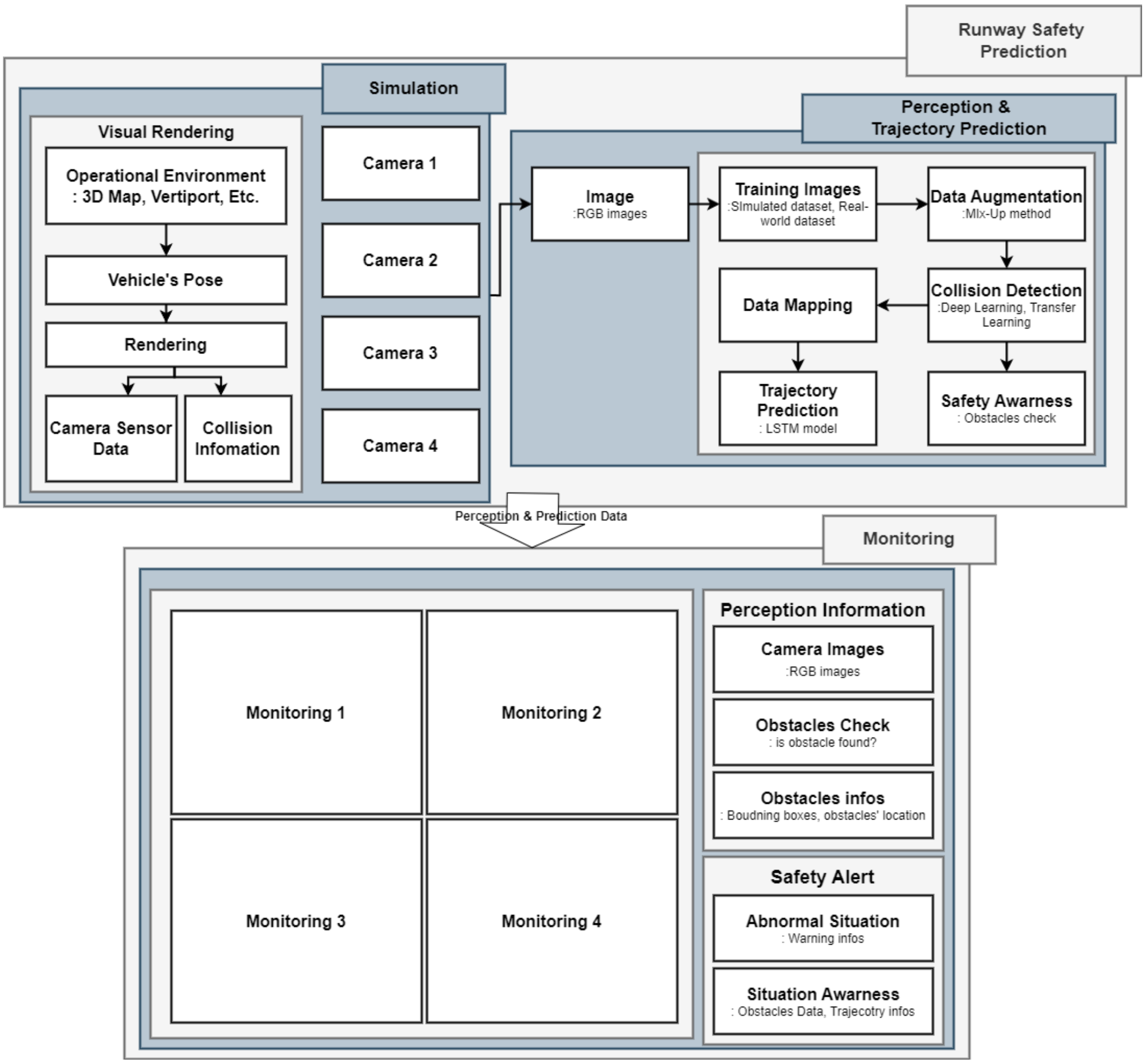


Figure 1 – Proposed Framework for Safety Runway Control Assistant System

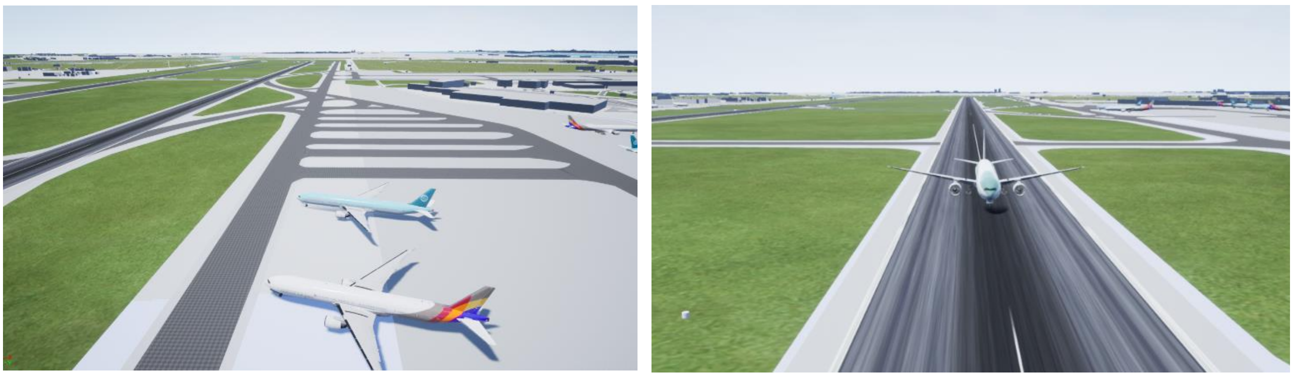
This work contributes to the progress in related fields in the following aspects:

- **YOLO-LSTM Detection Model**: Development and implementation of a YOLO-LSTM model that accurately detects and tracks obstacles around the runway using real-time data from four cameras. This includes the integration of advanced AI models to identify potential hazards such as aircraft, drones, and other foreign objects, providing immediate and precise detection capabilities.
- **Proactive Risk Avoidance**: Utilizing the combined strengths of YOLO for object detection and LSTM for sequence prediction, the system predicts the future trajectories of detected obstacles. This allows for anticipatory actions to avoid potential risks, enhancing the safety and reliability of takeoff and landing operations.
- **Enhanced Safety Measure:** The system's immediate and precise guidance abilities are expected to come into their own in these circumstances. Through the reduction of human error and utilization of data-driven insights, the system facilitates fast reactions, thereby supporting emergencies and providing increased safety in emergencies.

The system was trained and validated in a realistic simulator, which provided diverse situational image datasets. In the context of 3D modeling simulations, digital representations of physical objects, such as aircraft, runways, vehicles, and other objects, are created and incorporated into a data structure that replicates the physical environment. This ensured the reliability and adaptability of the deep learning models in real-world scenarios. The proposed framework aims to revolutionize runway safety management, reduce operator stress, and enhance decision-making processes, ultimately improving aviation safety standards and operational efficiency.

Simulation Development

To assure the safety and effectiveness of runway operations, the runway assistant safety environment, shown in Figure 2 uses cutting-edge technologies such as AI for system operation, high-reliability simulation, and specialized runway safety operation technology. These developments establish a robust foundation for the seamless integration of AI-supported systems into our aviation framework, ensuring efficient and secure aircraft operations throughout crucial takeoff and landing stages.



(a) (b)

Figure 2 – Simulation Environment for Runway Control Assistant System (a) Gimpo Airport (b) Takeoff runway

Using the AirSim Plugin together with the Unreal Engine, we configured our experiment to generate a simulated environment filled with a range of static and dynamic obstacles. Developed on the Unreal Engine, AirSim is an open-source, cross-platform program that makes creating incredibly realistic three-dimensional settings easier. The simulation environment that is produced has a thorough 3D map with many objects that replicate actual situations. The simulation's realism and adaptability are increased by the variety of pre-built scenarios offered by Unreal Engine, which represent various environments. Moreover, AirSim allows for software-in-the-loop (SITL) simulations, which work with popular flight controllers for unmanned aerial vehicle operations [9]. The development and testing of the runway assistant safety system depends on the building of a thorough and accurate simulation environment, which is made possible by this combination.

A modified version of the Seoul map was combined with the AirSim environment model to provide an environment modeling process breakdown. The technique recognizes the necessity of precisely simulating urban traffic dynamics, encompassing vehicle movement, and additional activities. Although emulating static and dynamic impediments has received the majority of attention, it is acknowledged that adding realistic traffic patterns will improve the simulation's realism.

In order to test the framework's object identification capabilities, occlusion effects were also added to create scenarios in which objects might be partially hidden from view. Considerable care was taken to guarantee that the simulation accurately represents variability in a variety of real-world dimensions, offering an extensive and accurate environment for the development and testing of the runway assistant safety system.

Data Mapping and Processing

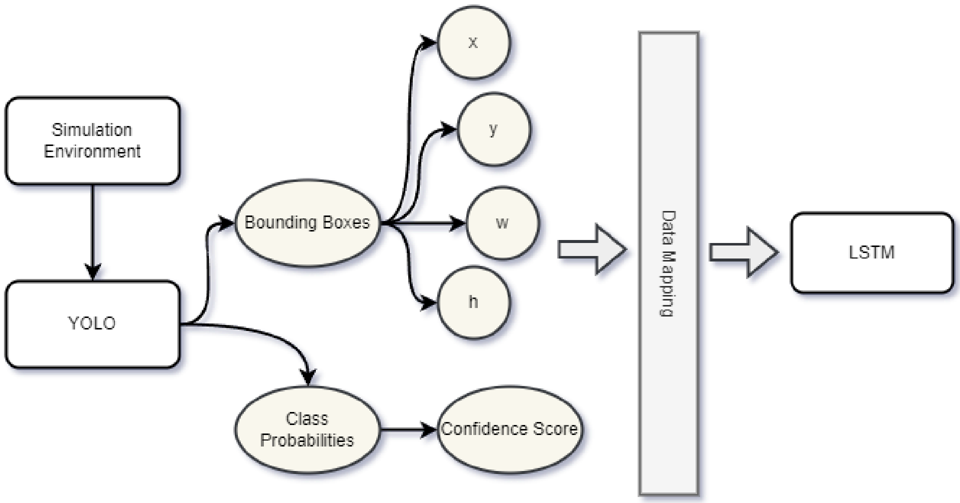


Figure 3 – Dataset Mapping and Processing

In order to generate our training dataset for the runway assistance system, we utilized virtual sensor cameras within a simulated setting to record an extensive range of situations and difficulties that arise during real-world runway operations as in Figure 3. By simulating the perspectives of sensors mounted on aircraft, these virtual sensor cameras captured RGB imagery. A thorough dataset that faithfully captures the intricacy of dynamic surroundings, including changing lighting conditions and meteorological influences, was generated using this methodology. The method of creating the dataset involved meticulous data augmentation and tagging procedures to guarantee both diversity and quality. The dataset was annotated with ground-truth labels for object detection tasks using robust labeling techniques, guaranteeing the precision and dependability of the training data. The dataset comprises images, label files, and object class files, each meticulously annotated to support the supervised learning process integral to the YOLO model. To elaborate further on the creation of the YOLO-LSTM dataset, we first transform the dataset produced by YOLO into a format appropriate for training the LSTM-based model. This dataset contains details like bounding box coordinates, objectness scores, and class probabilities for objects that are detected in each frame or timestamp. The procedure is taking a loop image of the movements of objects that are observed in order to generate sequential data that the LSTM model may use. Through the use of sequential data, the LSTM is able to predict future object trajectories by identifying temporal patterns and dependencies in object movement [10].

Detection Module

The detection module as in Figure 4 is responsible for identifying objects within an image, generating bounding box coordinates, class probabilities, and objectness scores. The output from this module undergoes a transformation process to train a model for predicting object behavior. This transformation involves several critical steps:

- Feature extraction: The process of identifying relevant characteristics from the detection outputs may have an impact on object behavior prediction. These may include motion patterns, velocities, or object trajectories.
- Temporal Sequences: These characteristics are combined into temporal sequences or state sequences that describe the object's behavior over time.
- Labeling Data: Describe the prediction task, such as estimating an object's future position, speed, or classification.

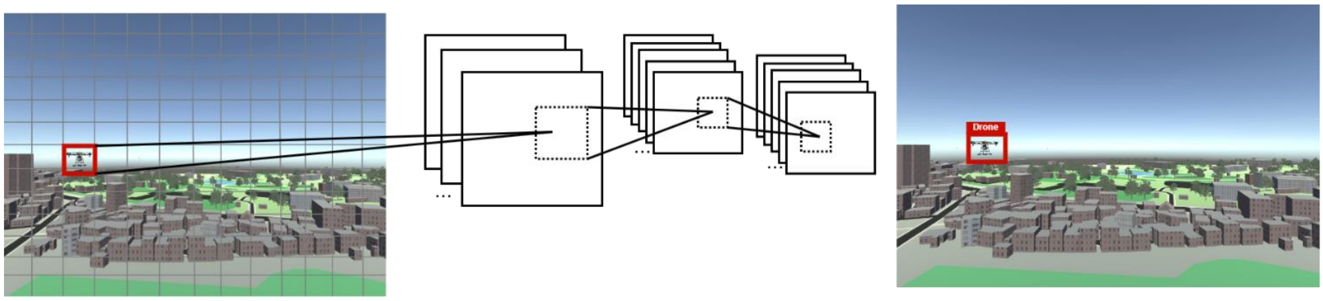


Figure 4 – Detection System

Prediction Module

Using a Long Short-Term Memory (LSTM) [11] network, one can predict how objects that have been spotted will behave. Because LSTM networks can capture long-term dependencies in data, they are a good fit for sequence prediction challenges. This technique, Figure 5, entails the following steps:

- Input Sequences: Sequences input into the LSTM network are the temporal sequences produced by feature extraction.
- Training: Using these sequences, the LSTM network is trained to identify patterns and forecast the objects' future states with accuracy.
- Output: Predictions about the objects' future locations, velocities, or classifications are produced by the trained LSTM network. For the purpose of predicting and responding to possible hazards on the runway, these predictions are essential.

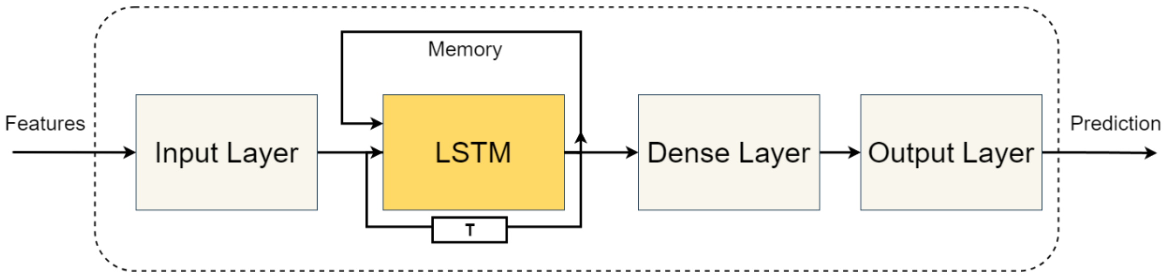


Figure 5 – Long Short-Term Memory

Additionally, the monitoring module enables operators to supervise and validate predictions made by AI, especially when it comes to identifying abnormal situations. The proposed Safety Runway Control Assistant System's conceptual design and workflow are shown in Figure 1. To create an overall system that improves runway operations' efficiency and safety, the framework incorporates several different components, including data collecting, detection, prediction, and monitoring.

The proposed framework aims to contribute to the advancement of aviation safety technologies by improving the safety and efficiency of the takeoff and landing stages by utilizing sophisticated data processing techniques, such as LSTM-based behavior prediction, and advanced simulation environments.

2.2 Methodology

The proposed framework for the Safety assistant system includes the integration of YOLO (You Only Look Once) and LSTM (Long Short-Term Memory) models as in Figure 6 for identifying and predicting the surroundings for aircraft to take off and land safely. The architecture of the proposed framework is shown in Figure 1. A comprehensive approach was used in the development of a Deep Learning-based Object Detection model to identify problems impeding flight safety. First, a variety of datasets covering both ground and aerial danger factors— possible threats— were gathered and carefully annotated. Preprocessing and augmentation are applied to these datasets to standardize formats and provide modifications that closely resemble real-world situations. The following step involves selecting a suitable Deep Learning architecture that is customized for object identification tasks, then adapting, and fine-tuning the model for both ground and aerial danger factors. To identify and categorize safety risks, appropriate architectures for object detection, such as You Only Look Once (YOLO), must be chosen and modified. A predictive model, such as Long Short-Term Memory (LSTM), is included after the detection model to predict object movement. The LSTM model learns from the input-output pairs, recognizing patterns and dependencies within the trajectory data. By capturing the object's motion dynamics, the model becomes proficient in inferring the future path of the obstacle. The proposed Safety Assistant System leverages models to not only identify potential runway risks but also predict aircraft behavior during takeoff and landing to avoid runway slides.

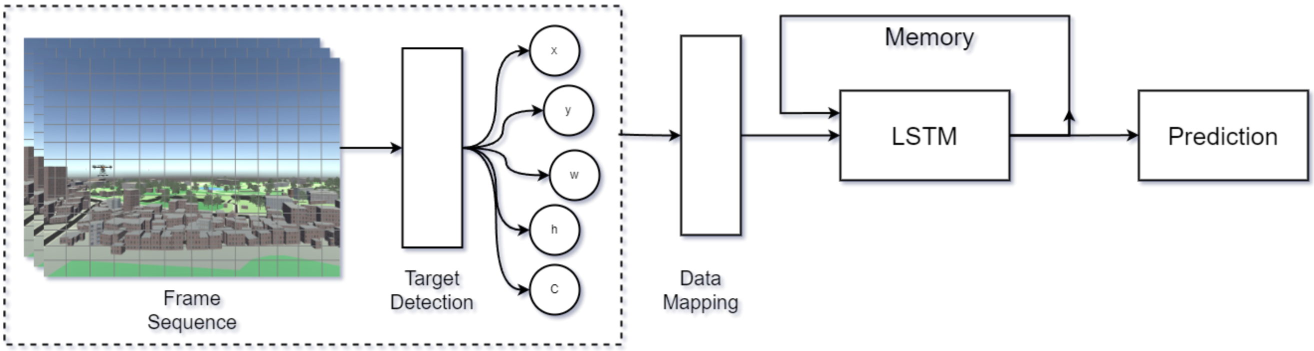


Figure 6 – YOLO-LSTM process diagram

Subsequently, the chosen YOLO outputs are combined and restructured into a structure that is consistent with the structure of the LSTM. Extracting essential data from a frame or timestamp for every detected object.

This contains information such as:

- Bounding Box Coordinates: (x, y, width, and height) representing the object's location and size.
- Objectness Scores: Indicating the confidence level that an object is within the detected box.
- Class Probabilities: Representing the categories of objects.

This involves representing the coordinates as center coordinates with width/height ratios and transforming them into relative values normalized within a given range. This confirms that the input data are consistent with the information required by the LSTM. Using YOLO outputs as directions, the data are arranged in a sequential format so that every component in the series reflects a time step. This procedure properly converts YOLO detection data into an LSTM-specific structured input format, which helps the LSTM model learn from previous detections and predict future object motions in the environment. The proposed method, Figure 7, greatly improves flight safety by enabling preventive safety measures and predictive analysis in Runway Control situations.

YOLO-LSTM based model

The YOLO model—more especially, YOLOv8 [12]—was chosen because of its cutting-edge object-detecting skills. The architecture of YOLOv8 is made up of multiple essential parts:

- Backbone Network: Taking feature maps out of the input image is the responsibility of the backbone network, CSPDarkNetBackbone. The enhanced feature learning and lower processing cost of CSPDarkNetBackbone contribute to YOLOv8's increased performance.
- Neck: The neck performs feature fusion functions and integrates contextual information, acting as a link between the head and the backbone. It aggregates feature maps derived from several backbone phases to create feature pyramids. To be more precise, the neck concatenates, or fuses features of different scales to help the network detect objects of different sizes; it also integrates contextual information to enhance detection accuracy by taking into account the larger scene context; and it lowers the dimensionality and spatial resolution of resources to speed up computation at the risk of lowering model quality.
- Head: The head uses these features to create class probabilities and bounding box predictions. For every object that is detected, it has layers that predict its bounding box coordinates, objectness score, and class probability.

Following object detection and data extraction by YOLO, an LSTM network is utilized to forecast the future motions of these objects. The architecture of the LSTM model consists of:

- The input layer receives sequential data with the YOLO output features included in each time step.
- LSTM Layers: Identify patterns and temporal connections in the sequence data. Gates in LSTM cells control information flow, preserving long-term dependencies and averting vanishing gradient issues.
- The output layer forecasts the locations, velocities, and classifications of the identified objects as well as their future states.

The LSTM cell's structure [13] includes three gates. New information will be added to the cell as each new input arrives and the input gate is turned on. Furthermore, the previous cell state c_{t-1} may also be "forgotten" if the forget gate ft was activated. It depends on whether the most recent cell output c_t propagated to the final state h_t is determined by the output gate o_t. Memory cells are used by the LSTM architecture to retain and process historical data in order to identify long-range temporal associations.

$$f_t = \sigma\left(W_f x_t + U_f h_{t-1} + b_f\right) \quad (1)$$

$$i_t = \sigma(W_i x_t + U_i h_{t-1} + b_i) \quad (2)$$

$$c_t = f_t * c_{t-1} + i_t * g_t \quad (3)$$

$$o_t = \sigma(W_o x_t + U_o h_{t-1} + b_o) \quad (4)$$

$$h_t = o_t * \sigma_h(c_t) \quad (5)$$

$$g_t = \sigma(W_c x_t + U_c h_{t-1} + b_c) \quad (6)$$

Where f_t, i_t, o_t are forget gate, input gate, and output gate; W_f, W_i, W_c and W_o are represented the weight matrices related to the gates; $U_f, U_i, U_c,$ and U_o denote the recurrent connections to the relative gates; $\sigma_g, \sigma_c, \sigma_h$ are activation functions.

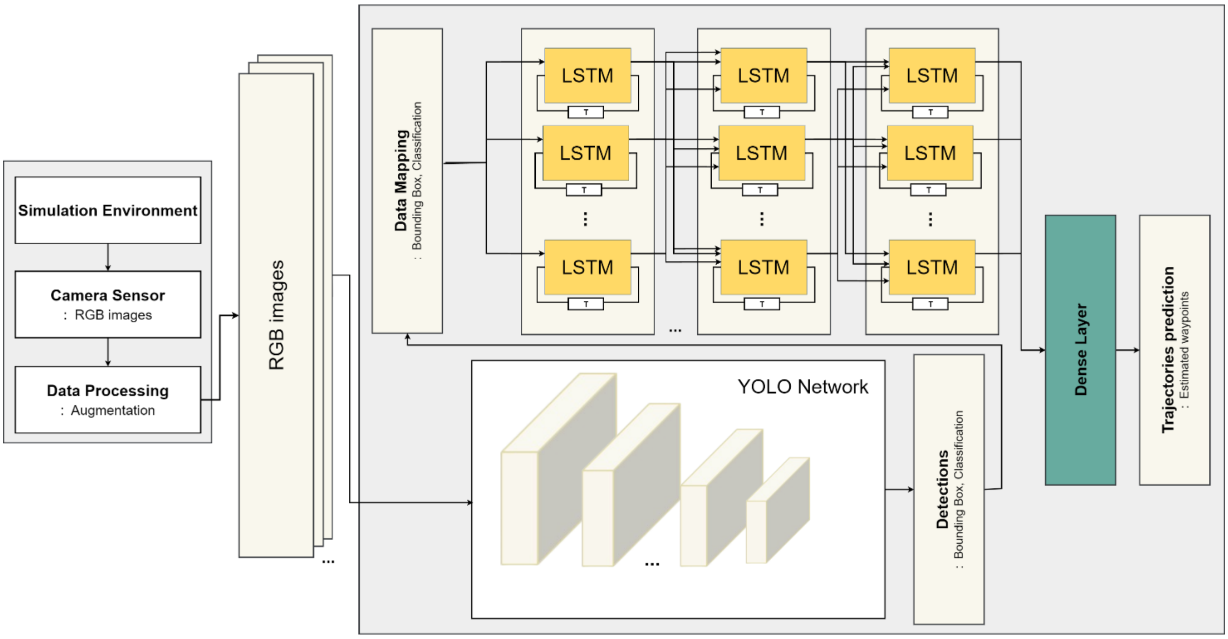


Figure 7 – Architecture of the proposed method

3. Experience Results

3.1 Performance & Result analysis

In this experiment, we established an environment that included a dynamic obstacle and a map. To evaluate situation awareness, training images were generated which simulate the virtual world. We used a simulator to generate training images in a virtual environment using a camera sensor, allowing us to create custom datasets for YOLO-LSTM-based training. In addition, this simulation provides a controlled environment in which we can generate accurate and diverse trajectory data for training purposes. Various metrics can be used to evaluate the performance of machine learning and deep learning models, such as the accuracy and mean average precision (mAP). In this study, we used the mAP to measure the accuracy of the object detector. The ground-truth bounding box was compared with the observed bounding box in the mAP calculation. Higher scores indicated higher detection accuracy. The mean average precision (mAP score) was calculated by taking the mean of the average precision (AP) or the overall intersection over union (IoU) threshold as in Figure 8 . The Root Mean Square Error (RMSE) was employed to assess the LSTM model's predictive ability in predicting the future positions of objects that have been spotted. A model's ability to forecast future positions is shown by its RMSE measure, whereby lower values correspond to more accurate predictions.

$$mAP = \frac{1}{n}\sum_{k=1}^{n} AveragePrecision_k \tag{7}$$

$$IntersectionUnion(IoU) = \frac{Aera\ of\ Overlap}{Aera\ of\ Union} \tag{8}$$

$$Precision = \frac{TP}{TP + FP} \tag{9}$$

$$Recall = \frac{TP}{TP + FN} \tag{10}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(Predicted_i - Actual_i)^2}{N}} \tag{11}$$

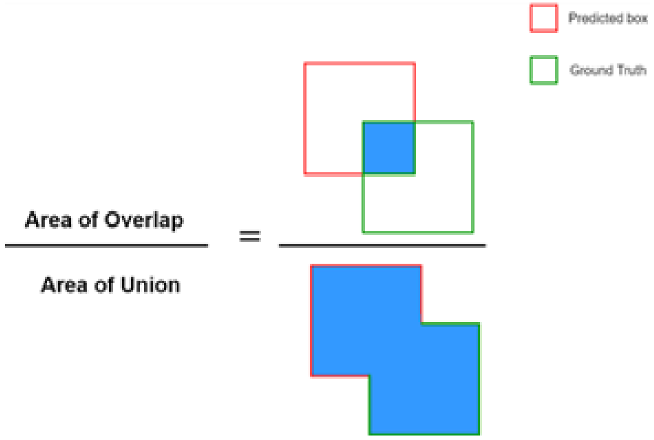


Figure 8 – Intersection Over Union

Our approach takes as inputs to the YOLO-LSTM model the bounding box coordinates (x, y, w, h) and class probabilities of identified objects at five historical points. Then the model predicts the class probabilities and bounding box coordinates for five future points in time. This ability to predict the future is essential for preventive runway control and safety monitoring.

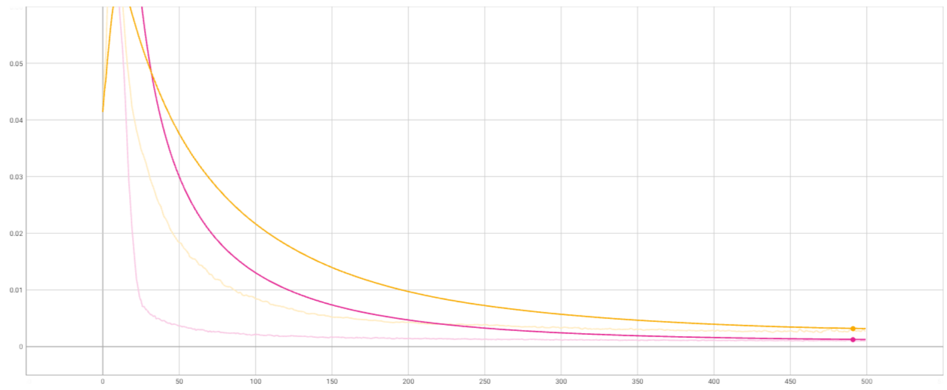


Figure 9 – Training and Validation Loss (Pink: Training Loss, Yellow: Validation Loss)

During the training process, the model's performance and convergence behavior were assessed by constantly evaluating the training and validation losses in Figure 9. The model was optimized for performance after experimenting with several hyperparameters, such as the initial learning rate, decay steps, decay rate, and optimizer. Through the use of adaptive learning rate modifications, this approach improved convergence and optimization throughout training. Early stopping was used as a regularization strategy to guarantee generalization and reduce overfitting. This included tracking the validation loss throughout training and stopping the process when, after a predetermined number of epochs, the validation loss stopped getting better. We utilized 80% of the data for training and 20% for the validation process. To demonstrate how closely the model's outputs match actual object

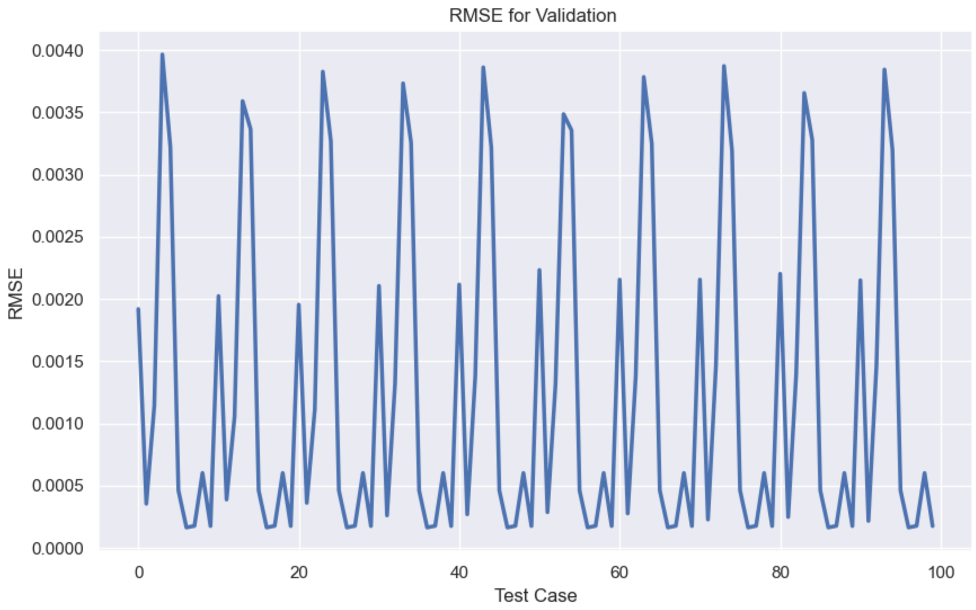


Figure 10 – RMSE for validation

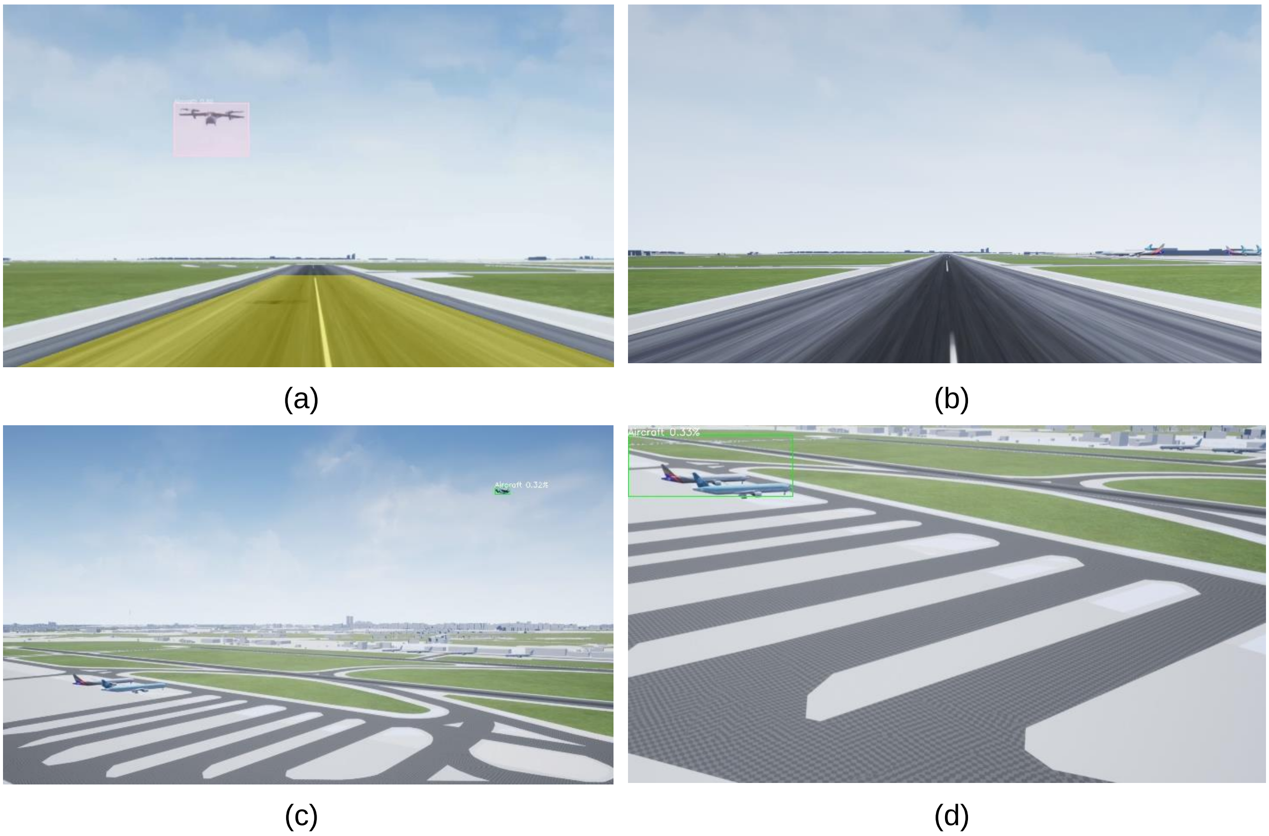
movements. Furthermore, Figure 10 displays the RMSE values for each test instance. The near-zero RMSE values indicate that the YOLO-LSTM-based model's predictions are very close to the actual trajectories, indicating the model's great accuracy and reliability in predicting future motions of identified objects.

In the test case scenario, we strategically put four cameras: one at either end of the runway, and the other two in the control tower, as shown in Figure 11. This arrangement enabled thorough coverage of crucial regions, enabling effective monitoring and data collecting across the runway environment. We strategically placed the cameras to guarantee that the whole length of the runway was under surveillance, allowing the integrated YOLO and LSTM systems to detect and track objects during takeoff and landing. Furthermore, the positioning of cameras in the control tower provided operators with significant insights into runway activities, improving situational awareness and allowing for informed decision-making. Overall, this deployment technique helped to validate the runway control assistance system's effectiveness and reliability in practical applications.

Figure 11 – Test Case Scenario

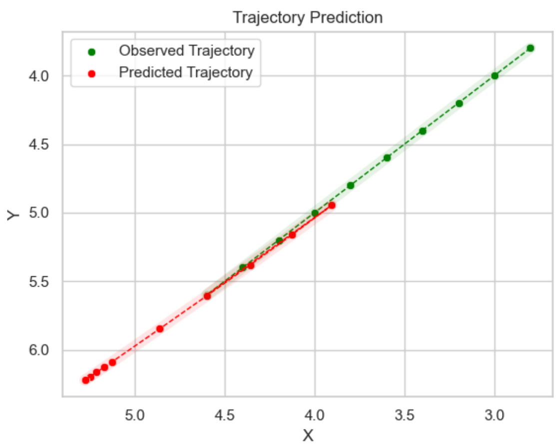
The results of the proposed experimental setup are demonstrated using bounding boxes overlay on visuals and item classification. Performance was evaluated using custom virtual datasets generated by the AirSim-Unreal simulator. The bounding boxes are color-coded to indicate identified items, with those corresponding to objects detected from various angles by the runway-installed cameras, as shown in Figure 12. It depicts a comprehensive representation of the monitoring perspectives acquired by each camera, providing extensive insights into the trajectory prediction process for recognized objects. This visual representation emphasizes the synchronized operation of several cameras, each offering distinct perspective points and data streams critical for accurate trajectory prediction. The system collects a wide range of visual data using this multi-camera configuration, allowing for a comprehensive comprehension of the object's motion dynamics. Based on the monitoring from cameras 1, 2, 3, and 4, cameras 1 and 3 identified the dynamic object. Figure 13 shows an extensive overview of the predicted results for the indicated objects. Figure 13(a) shows the trajectory prediction of the observed object from monitoring camera 1, whereas Figure 13(b) shows the prediction for the object from monitoring camera 3. In both figures, the green line shows the observed trajectory, while the red line represents the predicted future trajectory.

Furthermore, Figure 13(c) depicts the accuracy of object detection using a bar graph, with the x-axis representing the labels of the objects (Aircraft and Drone) and the y-axis indicating the accuracy for each. Figure 13(d) also shows the prediction accuracy for the recognized items, with a bar graph comparing the accuracy of trajectory predictions for planes and drones. This detailed investigation and visualization show the system's effectiveness in identifying and predicting object trajectories, which improves situational awareness and safety during runway control operations.

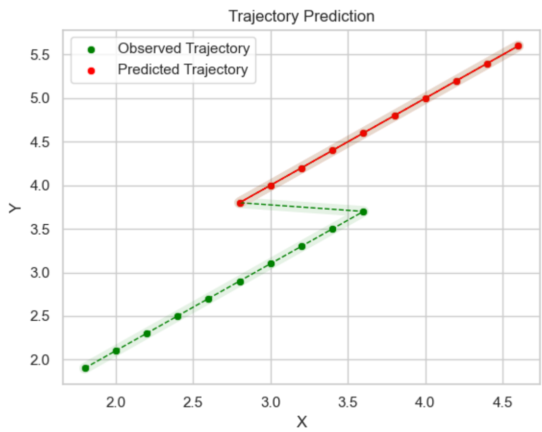


(a) (b) (c) (d)

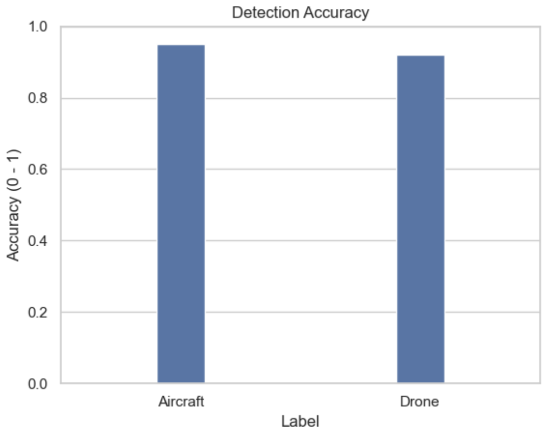
Figure 12 – Visual Representation of situational monitoring for the Safety Runway Control Assistant System (a) Monitoring 1, (b) Monitoring 2, (c) Monitoring 3, (d) Monitoring 4



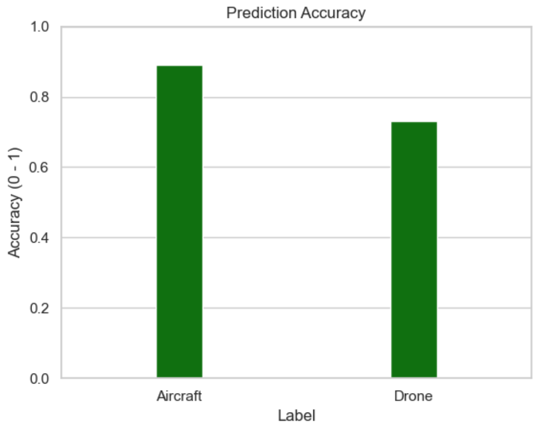
(a) Trajectory prediction from Monitoring 1



(b) Trajectory prediction from Monitoring 3



(c) Detection accuracy of identified objects



(d) Trajectory Prediction accuracy of identified objects

Figure 13 – Trajectory Prediction and Accuracy Analysis

4. Conclusion

The integration of the YOLO-LSTM method into the runway control assistance system has resulted in considerable improvements in operational efficiency and safety during takeoff and landing. The system combines real-time object identification with YOLO and predictive trajectory modeling with LSTM, providing accurate obstacle detection and movement predictions. This enhances situational awareness, enabling operators to prevent potential conflicts and ensure smooth operations during critical flight phases.

Comprehensive testing and validation using multiple cameras and customized virtual datasets have established the system's reliability and performance. The strategic placement of cameras ensures effective monitoring, and high predicted accuracy with near-one indicates the model's reliability in real-time runway safety monitoring. The demonstrated reliability and performance suggest readiness for real-world application, promising significant enhancements in aviation safety and operational efficiency.

In conclusion, the YOLO-LSTM-based runway control assistance system offers precise detection, accurate predictions, and enhanced situational awareness, contributing to safer and more efficient takeoff and landing operations. Comprehensive testing confirms its reliability, indicating its potential for real-world integration and substantial impact on aviation safety.

5. Acknowledgments

This work is supported by the Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Education (No. 2020R1A6A1A03046811).

6. Copyright Statement

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