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# Early Fire Detection Using a Convolutional Neural Network: Analysis of YOLOv11 and Roboflow 3.0 Performance

***Abstract*—Fires represent a critical global threat, impacting both urban areas and forest ecosystems. In recent decades, climate change has increased the frequency and intensity of these events, amplifying their consequences. Each year, fires burn millions of hectares of forests, releasing vast amounts of carbon dioxide and negatively affecting biodiversity and air quality. Fires in urban or structural areas not only pose risks to life and property but also generate high economic and social costs. Early fire detection has become essential to mitigate these devastating effects. This project used convolutional neural networks via Roboflow to analyze fire images, comparing models in classes such as nocturnal, forest, and structural fires to determine which case is more effective in network training. A fourth network was created by combining the previous classes with a total of 2,000 images, achieving a mAP of 97.2%. This project ensures precise detection and early fire detection.**

***Index Terms*—Convolutional Neuronal Network, Comparing Model, Early Fire Detection, Network Training, Precise detection.**

## I. Introduction

Fires will continue to be a critical global threat, affecting both urban areas and forest ecosystems. Each year, wildfires destroy millions of hectares of forest [1]. In 2024, a toxic layer was observed that affected most of Honduras, causing severe health consequences and an increase in fires. One notable incident was in La Tigra, where nearly 600 hectares of forest were destroyed, and hundreds of animals were burned. For this reason, the idea of early fire predictions using a convolutional neural network will be one of the automated methods to combat fires.

The Honduran Fire Department will provide fire-related images to strengthen the research. Regarding the program that will detect fires, Roboflow will facilitate the labeling and preparation of 2,000 fire images. The spiral methodology will be implemented, as it allows for gradual development and continuous incorporation of improvements for fire detection, enabling better understanding and enhancement of fire detection in various contexts.

A comparison between Roboflow and YOLOv11 will be conducted. Classes of fires such as structural, nocturnal, and forest fires will be merged, and training will also be carried out with each class individually to enable further comparisons.

## II. Context

### A. Problematic

Wildfires can arise from human carelessness, whether accidental or deliberate, as well as from cultural practices or natural phenomena. These fires can quickly engulf vast regions, inflicting severe harm on vegetation, wildlife, and soil, and resulting in substantial ecological, economic, and societal impacts [2].

The Ishikawa diagram is a visual tool used to analyze the issue of wildfires by identifying the primary causes that contribute to their occurrence, systematically organized into key categories to simplify the analysis process [3].

- Wildfire Prevention: Educate communities on fire management, promote safe practices like avoiding campfires in sensitive areas, and involve locals in forest brigades.
- Early Detection: Use IoT sensors, thermal-equipped drones, and AI-analyzed satellite imagery to monitor and predict fire risks.
- Response and Mitigation: Train firefighters and volunteers, and deploy helicopters with water systems and chemical retardants for effective firefighting.

### B. Current Level Analysis

Global Trends in Burned Areas: An analysis of trends in burned areas worldwide highlights that the countries with the largest annually burned areas are primarily located in Sub-Saharan Africa [4]. According to the study, approximately 70% of the total burned area globally occurs in Africa, largely due to savanna ecosystems and agricultural practices such as controlled burning, as shown in Figure 1.

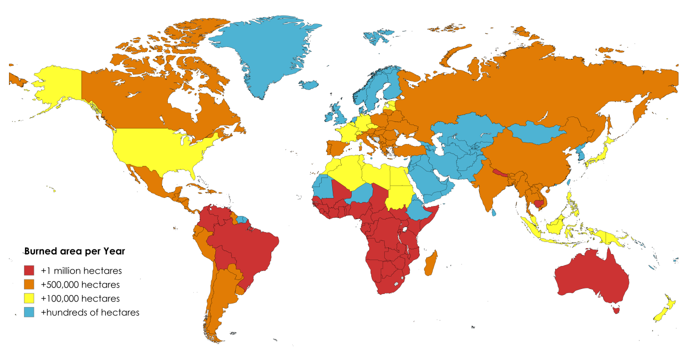


Fig. 1. Analysis of global fire areas by year.

The number of annual fires in Brazil, especially in the Cerrado and the Amazon, is significant. In recent years, more than 200,000 fires have been documented, depending on the intensity of the dry seasons and human activities. Brazil frequently tops the fire statistics in South America [5]. In figure 2, the fires that occurred in the Amazon, including the neighboring countries such as Brazil and others.

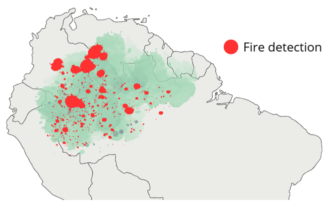


Fig. 2. Fire hotspots in the Amazon.

The main causes of fires in Honduras are both natural and human. Among the natural causes, dry weather and high temperatures are important factors that facilitate the spread of fire. However, human activities are a predominant cause, especially land clearing for agriculture, livestock, and other farming practices. These controlled or illegal burnings, particularly in rural areas, are a significant cause of wildfires. Furthermore, proximity to roads and paths increases the likelihood of fires, as they provide easy access for starting intentional fires [6]. In Honduras, the departments most affected by fires each year are mostly shown in Figure 3.

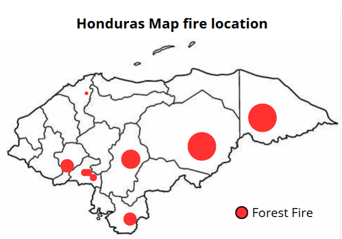


Fig. 3. Geographic location of concurrent fires in Honduras.

### C. *Deep Learning*

It is an advanced field within machine learning that uses deep neural networks to process large volumes of data and tackle complex challenges in areas such as computer vision, natural language processing, and other advanced applications. This approach has proven to outperform traditional machine learning methods, especially with unstructured data such as images, text, and audio [7].

### D. *Convolutional Neural Networks*

Convolutional Neural Networks (CNNs) are a type of deep neural network architecture specialized in processing data with a grid-like structure, such as images. These networks are fundamental in the field of computer vision, where they are used for tasks such as image classification, segmentation, and object recognition [8].

CNNs are capable of learning hierarchical features from data, enabling them to identify complex patterns in images, ranging from simple features like edges to more abstract patterns such as shapes and complete objects. [9].

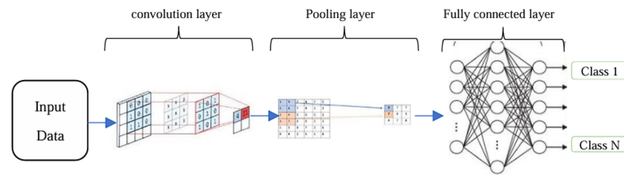


Fig. 4. Fully Connected Neural Network with Convolution and Pooling.

Each layer plays an important role in enabling a CNN to efficiently learn from data and perform tasks such as classification, segmentation, object detection, and more [23].

## III. Methodology

This chapter details the key aspects of the research, starting with the identification of variables. It covers the techniques and tools used in the study, the implementation of the most suitable methodology for the research, and the validation of the results.

### A. *Spiral Methodology*

After evaluating several options, the Spiral Methodology was selected for this research because it combines the strengths of sequential models, such as the waterfall approach, with the flexibility of iterative methods. This choice is particularly well-suited for projects where continuous risk analysis and ongoing feedback are critical.

The Spiral Model is a methodological framework for software development that blends both iterative and sequential elements. It was designed by Barry Boehm with the goal of enabling incremental progress in projects, ensuring consistent risk assessment and management throughout the development process. [10].

This model organizes work into iterative cycles, each of which includes stages of planning, risk analysis, development, validation, and review. This ensures that the product evolves in a controlled and effective manner [11]. Figure 5 illustrates the implementation of this methodology.

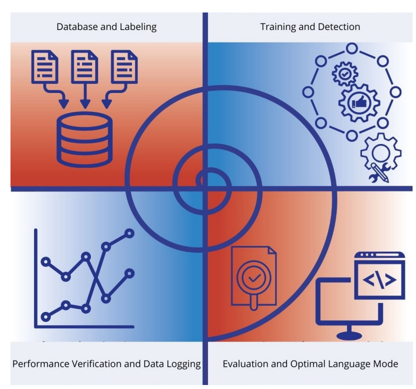


Fig. 5. Spiral Methodology for Projecting the Development of the CNN.

- Database and Labeling: Building a reliable database is a fundamental step in creating an effective fire detection model. This means gathering a diverse set of images that capture various fire scenarios, such as wildfires, building fires, and fires at night. This variety ensures the model can recognize fires in different environments. Equally important is the labeling process, where key elements like flames and fire hotspots are carefully marked to help the model learn accurately.

Roboflow for Organization and Labeling: Roboflow is a powerful tool for managing and labeling large image datasets efficiently. It lets users upload images from multiple sources and label them either manually or through collaborative features. Beyond that, Roboflow offers advanced data augmentation capabilities, automatically applying transformations like hue adjustments, cropping, and brightness changes. This creates additional training examples without the need to collect more images, saving time and effort [12].

- Training and Detection: Once the database is labeled, the next step is training the detection model to recognize fires in diverse conditions. The training images should include variations in saturation, exposure, resolution, and real-world scenarios like nighttime shots or unusual angles. This diversity helps the model generalize better, enhancing its accuracy and reliability when detecting fires in different situations [13].
- Evaluation and Optimal Language Model: After training, the model's performance is assessed using metrics like mAP (mean Average Precision) to evaluate its accuracy and ability to pinpoint fires. Integrating a language model can further enhance the system by interpreting the model's predictions and generating clear, actionable alerts. This ensures the system not only detects fires but also communicates findings effectively, enabling quicker responses in emergencies.
- Performance Verification and Data Logging: In this final stage, the model is tested in real or simulated conditions to measure its effectiveness. Key metrics like detection accuracy, response times, and error rates are recorded and analyzed. Roboflow simplifies this process by allowing direct evaluation of the model's performance using a test set of images. This step is critical to confirm the model works as intended and is ready for real-world deployment.

### B. Techniques and Tools Used

- A set of fire images has been collected from the Fire Department of Honduras, which will be used for analyzing the research. These images provide a detailed view of fires, which is essential for the learning process of the CNN.
- Roboflow is a computer vision platform that simplifies the creation, training, and deployment of machine learning models for tasks such as image classification, object detection, and segmentation. [14].

  Roboflow was used because it is an ideal tool for developing object detection, as it simplifies the preparation, organization, and annotation of images of wildfires, structural fires, and nighttime fires. It allows for augmentations such as saturation, brightness, exposure, and blur adjustments, helping to train models in diverse scenarios.

  Roboflow exports datasets in formats compatible with YOLO, optimizing the training process. It also allows for data splitting for validation and testing, ensuring model quality, and facilitates deployment on devices such as cameras or drones. It is a key tool for improving the precision and generalization of the model in fire detection projects [15].

### C. Variables and Metrics of Results

The mAP (mean Average Precision) is crucial in CNN research for fire detection due to its ability to provide a comprehensive and accurate evaluation of the model's performance. A high mAP score shows that the model is effective at accurately detecting fires while keeping false alarms and missed detections to a minimum. These aspects are crucial for safety and prevention, especially in high-stakes situations. Beyond that, mAP serves as a valuable tool for comparing different models and configurations, making it easier to refine the system as parameters are tweaked and more data is used for training. This metric is critical for ensuring the model's reliability in real-world applications, where timely and precise fire detection can make all the difference in protecting lives and property.

In the context of neural networks, the independent variable is the input dataset—the information the model uses to make predictions or classifications. It's called ”independent” because it stands on its own, not influenced by other factors within the model. Essentially, it's the raw data that fuels the learning process, allowing the model to identify patterns and make decisions [16].

- When the database isn't well-rounded—like when it lacks enough examples of nighttime fires or fires in buildings—the model has a harder time adapting to different situations. This often leads to a lower mAP score, which measures how accurately the model performs. Including a mix of varied and balanced images helps the model learn to spot fires in all kinds of settings, which boosts its mAP. If the dataset isn't thorough enough, the model might miss signs of fire in situations it hasn't seen before, making it less reliable and effective overall. In other words, the quality and variety of the data play a huge role in how well the model can do its job when it's needed most.
- Adjusting the size of images to a suitable scale, while keeping the proportions of objects intact, can boost both processing speed and the accuracy of fire detection in images of various sizes. This, in turn, helps improve the mAP score. By doing this, the model can work with different image dimensions without warping key details, making it more effective at identifying fires in diverse situations. Properly resizing images also helps find a sweet spot between keeping computational demands manageable and maintaining strong model performance [17].
- Using techniques like adjusting brightness, adding blur, tweaking hue, and modifying exposure can boost the

model's ability to handle different image conditions, which improves its mAP score—but only if these changes are kept within reasonable limits. For example, adjusting brightness and exposure helps the model adapt to varying lighting, but going too far can obscure crucial details. Adding a bit of blur can make the model more versatile, but too much blur can erase important features. Similarly, altering hue helps the model adapt to color changes, but extreme shifts can distort the true colors of a scene. When applied carefully, these adjustments help the model learn to deal with a wide range of conditions while maintaining its accuracy and reliability in detecting fires [18].

Result Metrics are key indicators used to evaluate and measure the performance of an object detection model (such as a fire detection model) in specific tasks. These metrics are essential for understanding how well the model is performing and how it can be improved. In the context of fire detection, the metrics help determine the accuracy with which the model identifies fire-affected areas and other important elements, such as fire hotspots [24].

- Precision: Precision measures how accurate the model's positive predictions are. In other words, it indicates how many of the predictions the model made as objects are actually correct [19]. As shown in equation (1).

$$P = TP/(TP + FP) \tag{1}$$

- Recall: The recall metric, also referred to as completeness or sensitivity, evaluates how well the model identifies actual positive samples. Specifically, it calculates the ratio of correctly detected positive instances (like real fires) to the total number of actual positives present. In simpler terms, recall tells us how many real fires the model successfully spotted out of all the fires that exist. It essentially reflects the model's ability to catch all relevant cases, ensuring nothing important is missed. This concept is further explained in equation (2).

$$P = TP/(TP + FN) \tag{2}$$

- mAP: It stands as a fundamental metric widely used to evaluate the performance of object detection algorithms. The calculation of mAP involves several steps, including the calculation of precision-recall for each class, constructing a precision-recall curve, and averaging the precision across all classes [20]. As demonstrated in equation (3).

$$mAP = \frac{1}{N}\sum_{i=0}^{N} AP_i \tag{3}$$

- F1-Score: It is the harmonic mean of precision and recall. It is used to obtain a single metric that combines both, which is useful when it's necessary to balance accuracy (precision) and coverage (recall). In many cases, especially in object detection tasks, the goal is to find a trade-off between not generating false positives (high precision) and not missing any important instances (high recall). As indicated in equation (4).

$$F1 = 2 \cdot \frac{\text{Precisión} \cdot \text{Recall}}{\text{Precisión} + \text{Recall}} \tag{4}$$

- False positives occur when the model predicts a fire where there is none, leading to unnecessary alarms. Minimizing false positives is important to avoid unnecessary alerts and ensure efficient resource use. On the other hand, false negatives happen when the model fails to detect an actual fire, which can have serious consequences. Minimizing false negatives is critical in fire detection applications to prevent risks and ensure safety [21].
- IoU (Intersection over Union): It measures the overlap between the bounding boxes predicted by the model and the real (labeled) bounding boxes of the detected objects. A high IoU indicates that the model's predictions are very close to the actual labels, which suggests good localization of fires in the images [22].

## IV. Results

As can be seen in the Table 1, the behavior of each training in Roboflow 3.0 had a constant value, even though the data value increased.

| **Roboflow 3.0 / Mix Fire + Augmentations / Train 9 resize 640x640** | | | | |
|---|---|---|---|---|
| **Train** | **Data** | **mAP** | **Precision** | **Recall** |
| 1 | 200 | 59.8 | 62.0 | 55.0 |
| 2 | 400 | 55.9 | 60.1 | 54.3 |
| 3 | 600 | 58.2 | 63.8 | 58.9 |
| 4 | 850 | 59.10 | 62.6 | 57.8 |
| 5 | 1100 | 55.9 | 60.5 | 54.5 |
| 6 | 1350 | 58.6 | 63.5 | 57.3 |
| 7 | 1600 | 59.11 | 62.7 | 57.9 |
| 8 | 1850 | 55.10 | 60.6 | 54.6 |
| 9 | 2000 | 97.1 | 98.0 | 94.2 |

TABLE I
TRAINING RESULTS WITH ROBOFLOW 3.0.

However, in Table 2, the values during each training session consistently increased as the image data was incremented, showing a clear and continuous growth of Yolov11.

| **YOLOv11 / Mix Fire + Augmentations / Train 9 resize 640x640** | | | | |
|---|---|---|---|---|
| **Train** | **Data** | **mAP** | **Precision** | **Recall** |
| 1 | 200 | 60.9 | 73.5.0 | 47.8 |
| 2 | 400 | 57.2 | 60.3 | 57.9 |
| 3 | 600 | 58.4 | 62.5 | 58.4 |
| 4 | 850 | 62.3 | 73.9 | 58.4 |
| 5 | 1100 | 63.6 | 72.1 | 59.4 |
| 6 | 1350 | 68.9 | 72.15 | 68.4 |
| 7 | 1600 | 71.4 | 73.1 | 69.5 |
| 8 | 1850 | 79.7 | 82.2 | 76.4 |
| 9 | 2000 | 97.2 | 98.5 | 93.6 |

TABLE II
TRAINING RESULTS WITH YOLOV11.

## V. Discusión

### A. Augmentations

Augmentations, such as adjustments in brightness, saturation, hue, and blur, were key to diversifying the training data and simulating real-world conditions. These techniques allow the network to be more robust when facing variations in images, such as changes in lighting or color due to flames.

### B. Image Resizing

The most determining adjustment was resizing the images to a specific resolution, which optimized the balance between input quality and model efficiency. This change was crucial in overcoming the previous accuracy limit faced by the networks. Specifically, it allowed the model to better understand the visual patterns of fires and achieve exceptional performance, reaching near-perfect values in important metrics.

### C. Differentiation Between Databases

Images for Training:

- Training with 65 Images: Slow and Gradual Progress.
- Training with 100 Images: Faster and More Notable Improvements.
- Training with 200 Images: Accelerated and Optimal Improvement.

### D. mAP Behavior in Fire Detection

In both networks, the mAP exhibits a progressive behavior, improving with the increase in training data. This is an expected behavior, as a larger amount of data allows the neural network to refine its ability to recognize specific fire patterns. However, there are significant differences in how this increase occurs between Yolov11 and Roboflow 3.0.

- mAP Behavior with Yolov11
  It positions itself slightly above Roboflow 3.0 in key metrics, showing robust performance and a superior balance between precision and sensitivity. Its ability to capture more details in complex images could be attributed to its architecture optimized for this type of task. In contrast, Yolov11 displays a more accelerated mAP behavior. From the early stages of training, the mAP values show more significant increases. This suggests that Yolov11 makes more efficient use of limited data during the initial phases, likely due to its architecture being more optimized for these tasks. At the end of the training, Yolov11 achieves a marginally higher mAP than Roboflow 3.0, establishing itself as the network with the best overall performance.
- mAP Behavior with Roboflow 3.0
  Although it had a slightly lower performance, it remains a very competitive solution. Its ease of use and integrated tools for preprocessing and augmentations facilitated the achievement of remarkable results.
  The mAP shows a more gradual and consistent growth as the data increases.
  During the early stages of training, the model appears to stabilize quickly, reaching values close to optimal, but with slower improvement after a certain point. While Roboflow 3.0 achieves competitive performance, it is observed to take longer to surpass certain critical thresholds (such as 80% mAP) compared to Yolov11..

## VI. Conclusions

The comparison between YOLOv11 and Roboflow 3.0 highlighted the individual advantages of each model. YOLOv11 achieved a mAP of 97.2%, slightly outperforming Roboflow 3.0 with a mAP of 97.1%. This positions YOLOv11 as the preferable option for applications where maximum precision is critical.

The spiral methodology allowed for an iterative evolution of the project, incorporating continuous adjustments based on result feedback. This approach facilitated the integration of improvements during the training and validation stages, maximizing the model's performance. Additionally, it allowed for testing different configurations and techniques, ensuring a gradual development adapted to the project's needs.

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## References

[1] Tyukavina, A., Potapov, P., Hansen, M. C., Pickens, A. H., Stehman, S. V., Turubanova, S., Parker, D., Zalles, V., Lima, A., Kommareddy, I., Song, X.-P., Wang, L., & Harris, N. (2022). Global Trends of Forest Loss Due to Fire From 2001 to 2019. Frontiers in Remote Sensing, 3, 825190. https://doi.org/10.3389/frsen.2022.825190

[2] Gil Mora, J. E. (2022). INCENDIOS FORESTALES: Causas e impactos. El Antoniano, 135(1), 68-113. https://doi.org/10.51343/anto.v135i1.866

[3] Campelo, A., Domingos, A., Júnior, Á., Silva, D., & Santos, M. (2022). PREVENÇÃO DE PERDAS: A FUNCIONALIDADE DO DIAGRAMA DE ISHIKAWA EM UMA LOJA DE DEPARTAMENTO. Revista Vox Metropolitana, 7, 192-207. https://doi.org/10.48097/2674-8673.2022n7p13

[4] Andela, N., Morton, D. C., Giglio, L., Paugam, R., Chen, Y., Hantson, S., Van Der Werf, G. R., & Randerson, J. T. (2024). The Global Fire Atlas of individual fire size, duration, speed and direction. Earth System Science Data, 11(2), 529-552. https://doi.org/10.5194/essd-11-529-2019

[5] Mayle, F. E., & Power, M. J. (2008). Impact of a drier Early–Mid-Holocene climate upon Amazonian forests. Philosophical Transactions of the Royal Society B: Biological Sciences, 363(1498), 1829-1838. https://doi.org/10.1098/rstb.2007.0019

[6] Valdez, M. C., Chang, K.-T., Chen, C.-F., Chiang, S.-H., & Santos, J. L. (2017). Modelling the spatial variability of wildfire susceptibility in Honduras using remote sensing and geographical information systems. Geomatics, Natural Hazards and Risk, 8(2), 876-892. https://doi.org/10.1080/19475705.2016.1278404

[7] Noor, M. H. M., & Ige, A. O. (2024). A Survey on State-of-the-art Deep Learning Applications and Challenges (No. arXiv:2403.17561). arXiv. https://doi.org/10.48550/arXiv.2403.17561

[8] Khan, A., Sohail, A., Zahoora, U., & Qureshi, A. S. (2020). A survey of the recent architectures of deep convolutional neural networks. Artificial Intelligence Review, 53(8), 5455-5516. https://doi.org/10.1007/s10462-020-09825-6

[9] Shiri, F. M., Perumal, T., Mustapha, N., & Mohamed, R. (2024). A Comprehensive Overview and Comparative Analysis on Deep Learning Models: CNN, RNN, LSTM, GRU (No. arXiv:2305.17473). arXiv. https://doi.org/10.48550/arXiv.2305.17473

[10] Ramos, J. A., Reyes-Duke, A. M., & Bardales, A. C. (2024). Convolutional neural network for dactylological alphabet recognition of Honduran Sign Language (LESHO). Innovare Revista de ciencia y tecnología, 1-5.https://doi.org/10.69845/innovare.v13i2.426

[11] Boehm, B. W. (1988). A spiral model of software development and enhancement. Computer, 21(5), 61-72. https://doi.org/10.1109/2.59

1 [12] Dzeng, R.-J., Cheng, C.-W., & Cheng, C.-Y. (2024). A
Scaffolding Assembly Deficiency Detection System with Deep
Learning and Augmented Reality. Buildings, 14(2), 385.
https://doi.org/10.3390/buildings14020385
18 [13] Hao, Y., & Jia, F. (2024). An Industrial Micro Parts Recognition Tech-
24 nology Based on Improved Yolov8. Journal of Physics: Conference Se-
ries, 2872(1), 012012. https://doi.org/10.1088/1742-6596/2872/1/012012
8 [14] Tripathi, R. N., Ramachandran, A., Agarwal, K., Tripathi, V., Badola, R.,
& Hussain, S. A. (2024). UAV and Deep Learning: Detection of selected
riparian species along the Ganga River. The International Archives of
the Photogrammetry, Remote Sensing and Spatial Information Sciences,
40 XLVIII-1-2024, 637-642. https://doi.org/10.5194/isprs-archives-XLVIII-
1-2024-637-2024
1 [15] Pham, D.-A., & Han, S.-H. (2024). Deploying a Computer Vision
Model Based on YOLOv8 Suitable for Drones in the Tuna Fishing and
1 Aquaculture Industry. Journal of Marine Science and Engineering, 12(5),
828. https://doi.org/10.3390/jmse12050828
12 [16] Messner, W. (2023). From black box to clear box: A hypothe-
sis testing framework for scalar regression problems using deep
artificial neural networks. Applied Soft Computing, 146, 110729.
https://doi.org/10.1016/j.asoc.2023.110729
28 [17] Talebi, H., & Milanfar, P. (2021). Learning to Resize Im-
36 ages for Computer Vision Tasks (No. arXiv:2103.09950). arXiv.
https://doi.org/10.48550/arXiv.2103.09950
10 [18] Yuan, N., Zhao, X., Sun, B., Han, W., Tan, J., Duan, T., & Gao,
X. (2023). Low-Light Image Enhancement by Combining Trans-
former and Convolutional Neural Network. Mathematics, 11(7), 1657.
https://doi.org/10.3390/math11071657
13 [19] Pérez-Aguilar, D. A., Pérez-Aguilar, Jair. M., Pérez-Aguilar, A. P.,
Risco-Ramos, R. H., & Malpica-Rodriguez, M. E. (2024). Inspección
de subestaciones eléctricas: YOLOv5 en la identificación de puntos
38 calientes. https://doi.org/10.17163/ings.n31.2024.04
14 [20] Reddy, S., Pillay, N., & Singh, N. (2024). Comparative Eval-
uation of Convolutional Neural Network Object Detection Algo-
rithms for Vehicle Detection. Journal of Imaging, 10(7), 162.
https://doi.org/10.3390/jimaging10070162
1 [21] Balamurugan, N. M., Kannadasan, R., Alsharif, M. H., & Uthansakul,
P. (2022). A Novel Forward-Propagation Workflow Assessment
Method for Malicious Packet Detection. Sensors, 22(11), 4167.
https://doi.org/10.3390/s22114167
22 [22] Wood, L., & Chollet, F. (2022). Efficient Graph-Friendly COCO Metric
Computation for Train-Time Model Evaluation (No. arXiv:2207.12120).
43 arXiv. https://doi.org/10.48550/arXiv.2207.12120
20 [23] Bonilla, Ó. S. O., & Duke, A. M. R. (2024). Convolutional Neu-
ral Network Modeling for Pest Detection in Corn Crops: Opti-
21 mization for Monitoring Efficiency. 2024 9th International Con-
21 ference on Control and Robotics Engineering (ICCRE), 334-338.
https://doi.org/10.1109/ICCRE61448.2024.10589895
46 [24] Ramirez Rios, F. E., & María Reyes Duke, A. (2023). Build-
7 ing of a Convolutional Neuronal Network for the prediction of
mood states through face recognition based on object detection with
YOLOV8 and Python. 2023 IEEE International Conference on Ma-
7 chine Learning and Applied Network Technologies (ICMLANT), 1-6.
https://doi.org/10.1109/ICMLANT59547.2023.10372862