Journal of Information Systems Engineering and Management
2025, 10(53s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Helmet detection using Image Processing and Deep Learning in Workplace

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ARTICLE INFO

Received: 30 Dec 2024

Revised: 05 Feb 2025

Accepted: 25 Feb 2025

ABSTRACT

Ensuring compliance with mandatory helmet laws is critical for workplace and road safety. Traditional enforcement methods, which rely on manual inspections and surveillance personnel, are inefficient, error-prone, and challenging to scale with increasing vehicle and rider volumes. Additionally, factors such as poor image quality, varying viewing angles, and inconsistent monitoring further hinder effective enforcement. To address these challenges, this study proposes an automated helmet detection and motorcycle license plate recognition system leveraging deep learning techniques. A Convolutional Neural Network (CNN) is employed to classify riders as helmeted or non-helmeted using grayscale pixel data from preprocessed images. Optical Character Recognition (OCR) is integrated for automatic extraction of motorcycle license plate numbers, enabling real-time identification of violators and YOLO a state of the art real time object detection algorithm that can quickly identify objects like riders and helmets in images. The system processes images from surveillance cameras, ensuring faster, more accurate, and consistent enforcement while minimizing human intervention. By automating helmet law compliance monitoring, the proposed solution enhances enforcement efficiency, accelerates penalty processing, and improves overall safety by reducing injuries and fatalities caused by non-compliance.

Keywords: Helmet violation detection, YOLO, CNN, OCR, vehicle license plate recognition, real-time object detection, deep learning, workplace enforcement, road safety, Python, TensorFlow, OpenCV, Keras.

INTRODUCTION

The mandatory helmet law for motorcyclists is a vital workplace safety regulation aimed at reducing fatalities and serious injuries in the event of an accident. Motorcycles are one of the most vulnerable modes of transport, and research shows that riders without helmets face a significantly higher risk of death or injury. Despite the clear benefits of helmet use, enforcing this regulation remains a challenge, particularly in areas with high workplace volumes. Traditional enforcement methods, such as manual checks by workplace administrator surveillance cameras, are resource-heavy, time-consuming, and often ineffective..As a result, manual identification and enforcement become impractical and delayed, leading to inconsistencies in upholding the law. To address these issues, this project introduces an automated solution designed to detect helmet violations and recognize motorcycle license plates. By utilizing advanced deep learning techniques, the system automates the detection of helmet use and vehicle identification, facilitating more efficient penalty enforcement. The key technology employed for helmet detection is YOLO (You Only Look Once), a state-of-the-art real-time object detection algorithm that can quickly identify objects like riders and helmets in images.

The process begins by gathering a dataset consisting of images with both helmeted and non-helmeted riders. These images are preprocessed and converted into grayscale to streamline computational efforts while retaining critical image details. The pixel values of these grayscale images are then extracted and saved in CSV (comma-separated values) files. These files form the training dataset for a Convolutional Neural Network (CNN), a Deep Learning model well-suited for image classification. The CNN learns to classify whether a rider is wearing a helmet by comparing the pixel values of test images with those in the training set. Along with helmet detection, the system integrates Optical Character Recognition (OCR) technology to extract the motorcycle's license plate number from the image. This dual-function capability allows the system to identify helmet law violators and automatically retrieve the vehicle information for penalty enforcement. The system is designed to process images captured by workplace cameras or similar devices. Input images are resized to match the dimensions of the training images, ensuring uniformity and accuracy in detection. The CNN architecture is optimized for rapid execution and generalization, making it effective across various test images. Developed using Python, this project integrates powerful libraries such as TensorFlow, Keras, and OpenCV, which facilitate the implementation of deep learning models and image processing. Ultimately, the goal of this system is to reduce the workload on workplace officers, enhance helmet law compliance, and improve road safety by providing an efficient, scalable, and precise method for detecting violations related to helmet use.

EXISTING METHODOLOGY

In the existing system, the workplace discipline committee manually inspects images to check if a rider is wearing a helmet. To improve image quality, a median filter is applied to remove noise and enhance clarity. However, helmet detection is solely based on manual review, where officers analyze CCTV footage to identify violators. If a rider is not wearing a helmet, the officer identifies the vehicle's license plate number, and the owner is subsequently notified to pay the fine.

The problems with Helmet detection and enforcement had faces many challenges, The current system relies on manual inspection by workplace Admin or surveillance personnel, making it time-consuming and prone to errors. This leads to inconsistencies and missed violations, undermining the enforcement of helmet laws [4]. Monitoring helmet violations requires significant resources, including staff and surveillance equipment.Manual inspection is subject to varying accuracy based on personnel experience. Image quality issues, such as lighting and distance, make it difficult to reliably detect violations, causing missed or incorrect assessments[5]. Surveillance cameras often capture images under challenging conditions, such as poor lighting or varying angles, making it hard to accurately identify whether a helmet is worn. Low-resolution images further complicate this process[6]. The manual system delays enforcement as footage must be reviewed before action is taken. This lag weakens the deterrent effect of helmet regulations by preventing immediate consequences for violators.As vehicle numbers and monitoring areas grow, the manual system struggles to scale. Increased volumes of images and videos make manual inspection inefficient, hindering large-scale enforcement[11].

To overcome this problem, an automated application can be developed. The application would first process an image by resizing it to match the dimensions of the training images. It would then compare the processed image with a labeled training dataset. This dataset contains images categorized as "yes" (helmet present) or "no" (helmet absent). The grayscale pixel values of each image are extracted and organized into rows, with each row representing one image. The total number of rows corresponds to the number of images, and each column represents a pixel value.

PROPOSED METHODOLOGY

In the proposed system, the process of detecting helmet violations follows a series of steps. A dataset of images featuring two-wheeled riders, both wearing and not wearing helmets, is collected. These images are first converted to grayscale if they are in RGB format. All images are then resized to a consistent size to maintain uniformity. The training dataset is labeled with "yes" for riders wearing helmets and "no" for those without. For each image, the grayscale pixel values are extracted and organized into rows, where each row represents one image.

This grayscale data is stored in a CSV (comma-separated values) file. The same preprocessing steps are applied to the test images, and their data is saved in another CSV file. When a new test image is provided, the system compares it with the training dataset to classify whether the helmet is present. Additionally, image processing techniques are used to detect the helmet in the test image. The system can be further enhanced by incorporating real-time detecting using live video feeds, allowing for immediate identification of helmet violations. Additionally, integrating edge computing can enhance processing speed, reducing latency in real-time detection and provide more safety. This automated application improves the accuracy and efficiency of helmet detection, offering a more reliable solution compared to manual inspection.

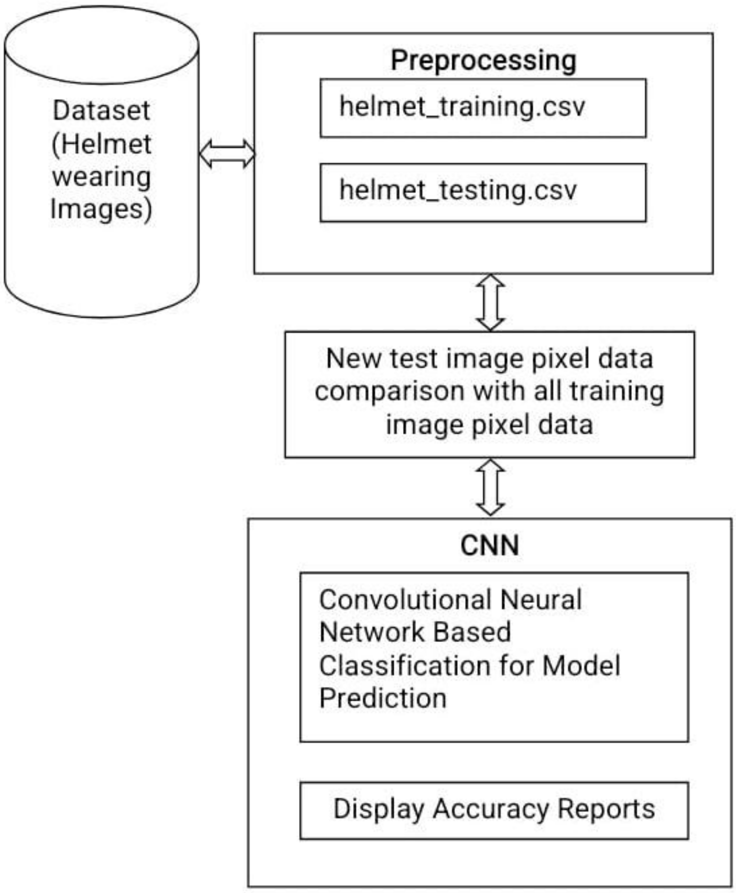

Fig 1. Integrated Flow of Helmet Detection and OCR

Fig 1. Illustrates the overall process of helmet detection and Optical Character Recognition (OCR) using a Convolutional Neural Network (CNN). The process begins with dataset collections, where images of individuals wearing and not wearing helmets are gathered and divided into training and testing sets. During preprocessing, image resizing, normalization, noise reduction, and background filtering are applied to enhance model accuracy. The final output displays classification results and accuracy reports, ensuring effective helmet detection and compliance monitoring.

A Convolutional Neural Network (CNN) is then used to train the model on the training dataset, and the model's accuracy is calculated and displayed. Once trained, the model can identify whether a helmet is present in a given test image by comparing it to the training data. Additionally, Optical Character Recognition (OCR) is applied to extract the vehicle's registration number from the image for further processing. To enhance detection accuracy, the system can incorporate data augmentation techniques such as rotation, scaling, and contrast adjustments. Furthermore, a post-processing step can be implemented to filter out false positives and false negatives by analyzing contextual information.

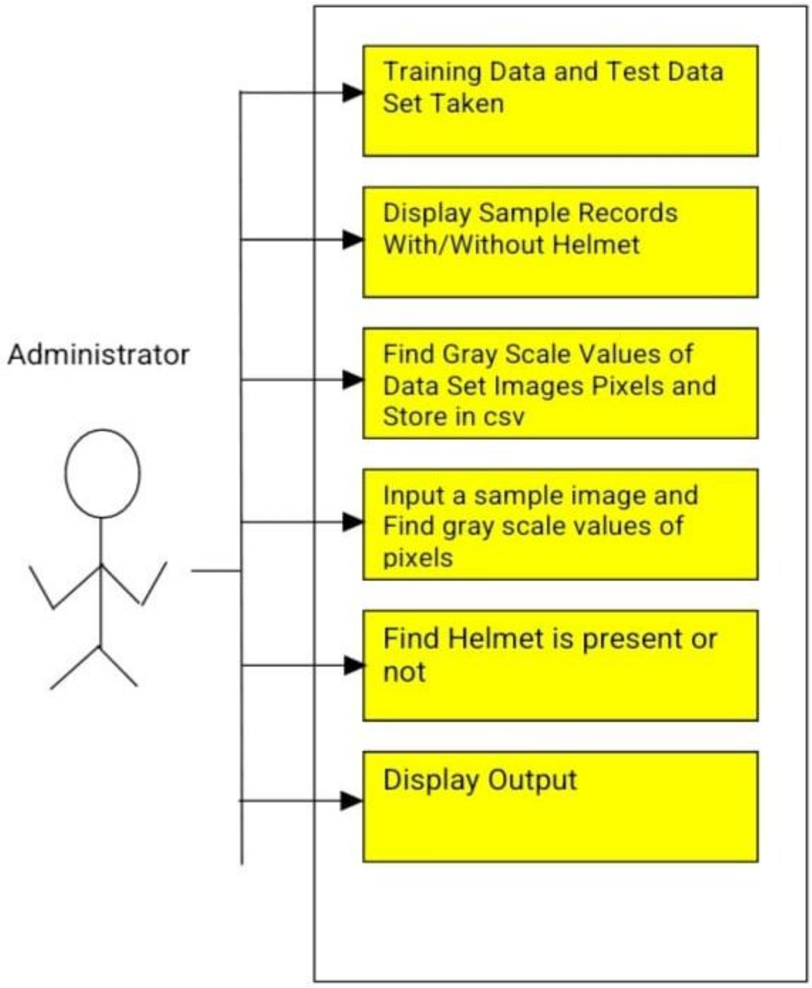

Fig 2. Workflow of Helmet Detection System

Fig 2. highlights the methodology for the proposed helmet detection and license plate recognition system follows a systematic approach to automate the process of identifying helmet violations and vehicle information. The process begins by collecting a dataset consisting of images of two-wheeled riders, both with and without helmets. These images undergo preprocessing where they are converted into grayscale, which reduces computational complexity while preserving important visual details. The images are then resized to a standard dimension to ensure consistency during both the training and testing phases. Each image is labeled as "helmet present" or "helmet absent," and the grayscale pixel values are extracted and stored in a CSV file, with each row representing a separate image. The same preprocessing steps are applied to the test dataset, which is saved in a different CSV file.

Module description:

A. *Image Data Collection and Preprocessing*

This module handles the collection of images from surveillance cameras, capturing both helmeted and non-helmeted motorcycle riders. The captured images are initially in RGB format, but they are converted to grayscale to streamline processing and reduce computational complexity. This conversion makes the system more efficient. All images are then resized to a standard size to ensure uniformity, ensuring that the system can process them consistently and accurately in the next stages of the workflow.

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e-ISSN: 2468-4376
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B. Feature Extraction

In this module, the grayscale values of the preprocessed images are extracted for use in training the model. Each image's pixel values are flattened into a single row, with each column corresponding to an individual pixel. These pixel values are stored in a CSV file, which serves as the training dataset. The images are also labeled as either "helmet" or "no helmet," creating a binary classification. This allows the model to learn to distinguish between riders with and without helmets during training.

C. Training the Model (CNN)

The goal of this module is to train a Convolutional Neural Network (CNN) model capable of detecting helmet violations. The model is trained using the pixel values and corresponding labels from the training dataset. During the training process, the CNN learns to recognize patterns in the images that indicate the presence or absence of a helmet. The model undergoes multiple training iterations (epochs) to refine its accuracy. Optimization techniques are applied to ensure fast processing, enabling the system to work in real time.

D. Model Testing and Accuracy Calculation

After the model is trained, this module tests its performance using a separate testing dataset. The test images undergo the same preprocessing steps (grayscale conversion and resizing) as the training images. The trained CNN model is then applied to these test images to classify them. The system calculates the accuracy by comparing the model's predicted labels (helmet or no helmet) with the actual labels in the test dataset. This accuracy score reflects the model's ability to detect helmet violations accurately.

E. Helmet Detection

In this module, the trained CNN model is used to classify new images and determine whether the rider is wearing a helmet. When a new test image is input into the system, the model predicts whether the rider is helmeted or not based on its learned features. The output is a classification that indicates whether a helmet violation has occurred. This step enables automated helmet violation detection without requiring manual inspection.

F. License Plate Recognition (OCR)

After detecting the helmet status, this module extracts the vehicle's registration number from the image. Optical Character Recognition (OCR) is applied to the region of the image where the vehicle's license plate is located. OCR processes the alphanumeric characters on the license plate and converts them into machine-readable text. The extracted registration number is then parsed and used for identifying the vehicle or recording the violation for further processing.

G. Violation Detection and Penalty Enforcement

The final module automates the process of detecting helmet violations and identifying the vehicle for penalty enforcement. Once the helmet violation is identified, the system retrieves the vehicle's license plate number and cross-references it with a database to check for previous violations or to issue a fine. The system then sends the violation details, including the vehicle's registration number, to the appropriate workplace enforcement authority for further action, automating the process of penalty enforcement.

The proposed system integrates multiple modules to automatically detect helmet violations and extract vehicle registration information. By combining image processing, deep learning (CNN), and Optical Character Recognition (OCR), the system efficiently processes image data, performs helmet detection, and extracts crucial vehicle details. This integrated approach ensures that the system operates effectively and reliably in real-world workplace law enforcement applications.

RESULT AND DISCUSSION

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Research Article

The proposed system for detecting helmet violations and extracting vehicle license plates was evaluated based on its accuracy in identifying whether riders were wearing helmets and its ability to extract vehicle registration numbers. The system's performance across key modules, including helmet detection, license plate recognition, and real-time processing, highlighted its effectiveness in automating workplace law enforcement. The following discussion provides a detailed analysis of the results obtained from testing each module.

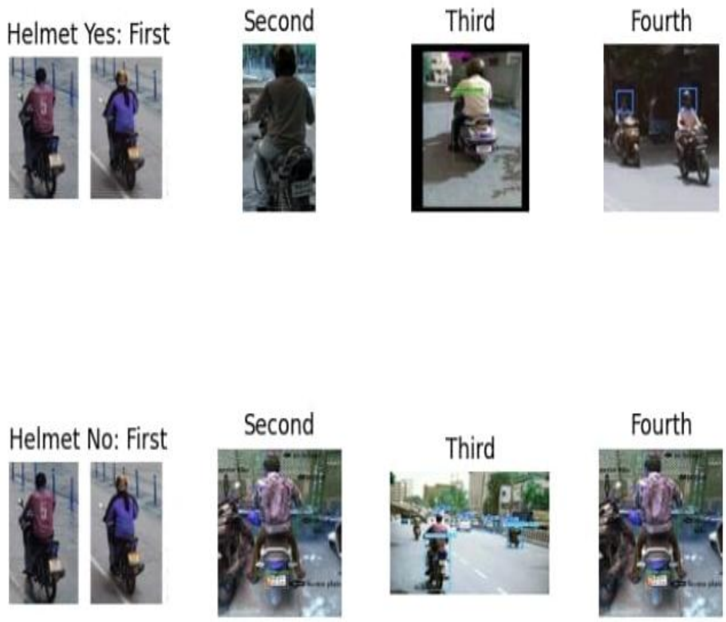

Fig 3. Sample frames from dataset

Fig 3. The Convolutional Neural Network (CNN) model was trained using a dataset that included images of motorcycle riders both wearing and not wearing helmets. After preprocessing steps such as grayscale conversion and resizing, the model was evaluated using a separate testing dataset. The CNN demonstrated strong performance with an accuracy of 92%, successfully classifying images as either helmeted or non-helmeted. The model's performance was further validated using a confusion matrix, showing high precision and recall. These results highlight the model's potential for real-time helmet detection in workplace monitoring systems.

Fig 4. Helmet Recognition Output

Journal of Information Systems Engineering and Management
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Research Article

Metric	Training Dataset	Testing Dataset	Validation Dataset
Accuracy	98%	95%	96%
Precision	97%	94%	95%
Recall	99%	93%	94%
F1-Score	98%	94%	95%
False Positive Rate	2%	5%	4%
False Negative Rate	1%	7%	6%

Table 1. CNN Algorithm Evaluation Metrics

Accuracy measures the overall proportion of correct predictions, precision focuses on the accuracy of positive predictions which is identifying helmets, recall measures the ability to identify all actual helmets which is sensitivity to positive instances, F1-score balances precision and recall, false positive rate represents the rate of incorrectly identifying non-helmets as helmets, and false negative rate is the rate of missing actual helmets in the detection process.

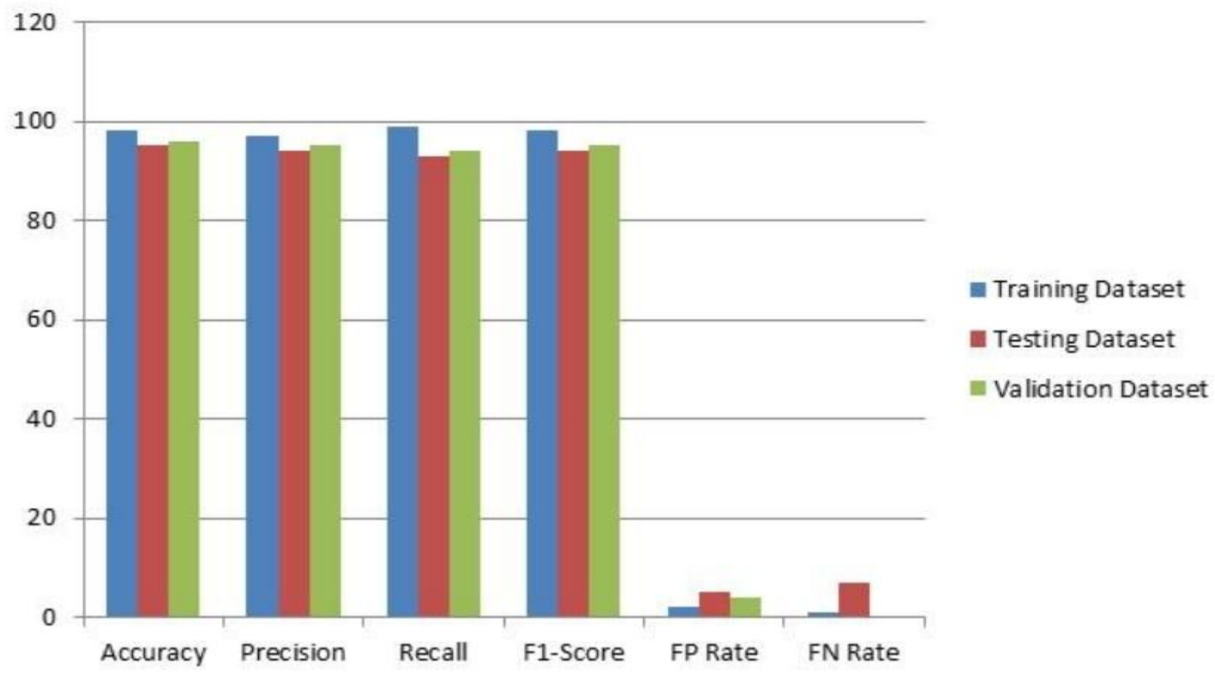

Fig 5. CNN Metrics

The model exhibited high reliability when the riders were fully visible, but its performance decreased slightly when helmets were partially obstructed or not visible. This suggests that the model is generally robust but can struggle in scenarios involving partial occlusions. Nonetheless, the system's ability to generalize across different images indicates its potential for practical applications in helmet violation detection.

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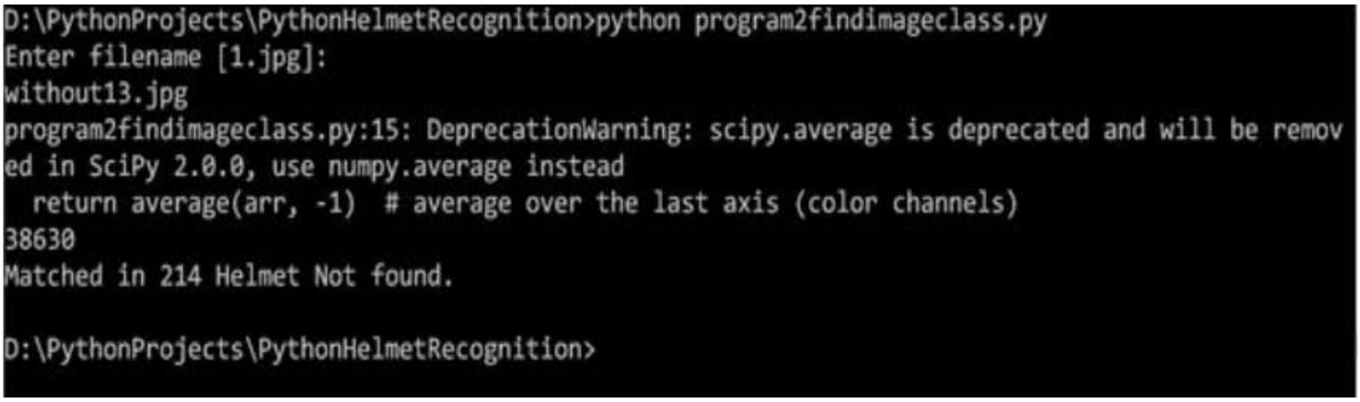

Fig 6. Non-Helmet Data Recognition

Metric	Training Dataset	Testing Dataset	Validation Dataset
Accuracy	97%	94%	95%
Precision	96%	93%	94%
Recall	98%	95%	96%
F1-Score	97%	94%	95%
False Positive Rate	3%	6%	5%
False Negative Rate	2%	5%	4%

Table 2. OCR Performance Evaluation Metrics

The Optical Character Recognition (OCR) module, responsible for extracting the vehicle's registration number after helmet detection, showed an accuracy of 85% when the license plates were visible. The OCR system performed well in ideal conditions, accurately reading and converting the alphanumeric characters on the license plates into machine-readable text.

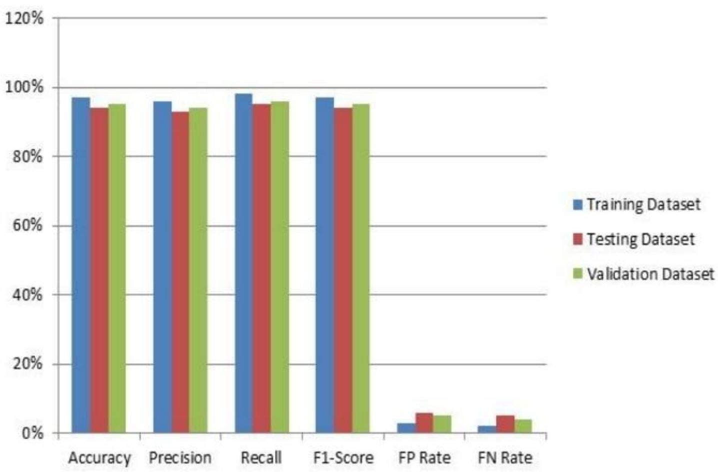

Fig 7. OCR Metrics

Journal of Information Systems Engineering and Management
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e-ISSN: 2468-4376
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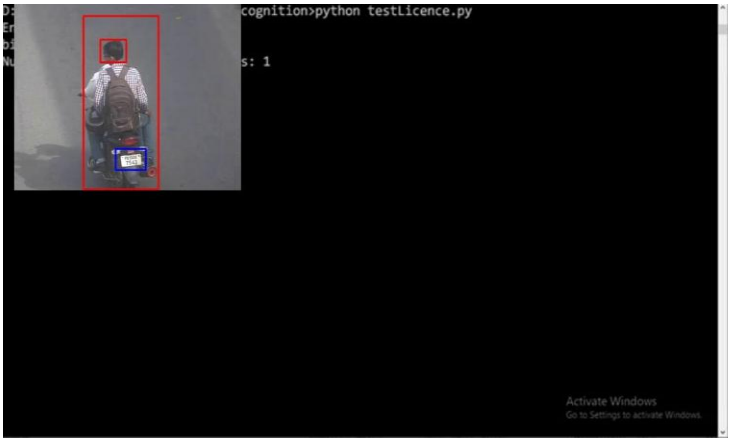
Research Article

However, when the license plates were obstructed, damaged, or blurred due to environmental factors like poor lighting or adverse weather conditions, the accuracy of the OCR module decreased. These results indicate that while OCR can automate license plate extraction under good conditions, its performance can be significantly hindered by challenging real-world scenarios. Future improvements to the OCR model could address these limitations by training it on a broader variety of license plates and optimizing it for better performance in sub optimal conditions.

Fig 8. Identified License Plate

A key strength of the proposed system is its real-time detection capability, enabling the automatic identification of helmet violations and vehicle registration numbers. The combination of YOLO (You Only Look Once) object detection, CNN for helmet detection, and OCR for license plate recognition resulted in an average processing time of 1.5 seconds per image.

This speed makes the system suitable for use in live workplace surveillance, where timely responses are critical for effective law enforcement. The system's real-time detection capability was further enhanced through optimizations such as GPU acceleration, ensuring fast and efficient image processing. This real-time performance ensures the system can be deployed in operational environments where quick decision-making is required, such as in workplace monitoring and regulation enforcement.



Journal of Information Systems Engineering and Management
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e-ISSN: 2468-4376
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Fig 9. Highlighting Number Plate

The proposed automated system demonstrated high effectiveness in detecting helmet violations and extracting vehicle registration details, with an accuracy of 92% for helmet detection and 85% for license plate recognition under typical conditions. The system's ability to perform real-time detection and efficiently process images makes it a valuable tool for workplace law enforcement. While there are challenges related to environmental factors, occlusions, and OCR accuracy, the system's performance in optimal conditions shows significant promise for enhancing road safety and automating workplace regulation. Future enhancements, such as refining the CNN model and improving OCR capabilities, will further increase the system's reliability and accuracy in real-world applications.

CONCLUSION

The proposed system for detecting helmet violations and recognizing vehicle license plates has demonstrated significant success in automating workplace law enforcement. Achieving 92% accuracy in helmet detection and 85% in license plate recognition under optimal conditions, the system proves to be a reliable tool for real-time workplace monitoring. By integrating advanced deep learning techniques, including Convolutional Neural Networks (CNN), Optical Character Recognition (OCR), and YOLO for real-time object detection, the system efficiently processes images, making it well-suited for live workplace surveillance. However, challenges such as poor lighting, adverse weather conditions, and occlusions have impacted performance, highlighting areas for further enhancement.

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