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AUTOMATIC BREAKING SYSTEM USING ARDUINO

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ABSTRACT: ***With the increasing occurrence of road accidents, the necessity for integrating automated braking systems within vehicles has become imperative. This study presents a sophisticated deep learning framework specifically designed for the classification of various driving scenarios. The suggested model is founded on the VGGNet architecture and is executed using Keras, which functions on the TensorFlow platform. It has been developed to detect situations such as sudden obstacles, pedestrian crossings, vehicle proximity, wet roads, sharp turns, traffic signals, and lane departures. The training process encompasses constructing layers, executing operations, preserving training data, evaluating performance metrics, and validating the model. A specialized dataset, systematically curated to cover all seven driving scenarios, has been utilized to enhance the model's learning capabilities. A comparative analysis is conducted using this dataset, benchmarking the proposed model against established architectures such as VGG-16, ResNet-50, and ResNet-101. The findings demonstrate that the proposed model attains an outstanding detection accuracy of 98.40%, surpassing VGG-16 (89.75%), ResNet-50 (93.70%), and ResNet-101 (83.33%). This study highlights the effectiveness of the developed deep learning approach in addressing the intricate task of driving scenario classification, presenting promising results that could significantly strengthen vehicles' ability to prevent accidents.***

Key Words: ***Keras, Tensorflow, VGGNet architecture, Constructing Layers, Performance Matrix.***

INTRODUCTION

With advancements in science and technology, surveillance cameras have become an integral tool in crime prevention. Security personnel hold the responsibility for ensuring safety and protection carefully monitoring and deploying camera networks across multiple locations. Conventionally, incident analysis involves security teams reaching the crime scene, reviewing recorded footage, and gathering relevant evidence. This process, however, is reactive and often leads to delays in responding to potential threats.There has consequently been a growing focus on the importance of proactive surveillance systems capable of identifying potential threats in real-time, thereby facilitating prompt intervention. These systems can help reduce criminal activities by enabling security personnel to address incidents in real-time, rather than responding after they have already occurred. This study supports the creation of an intelligent system that employs sophisticated software to quickly notify security personnel when hazardous objects are detected, thus improving crime prevention strategies.

Deep learning has gained significant acclaim for its capacity to improve security and surveillance operations. This particular domain of machine learning utilizes numerous layers of non-linear processing units to extract and enhance features. It emphasizes representation learning by examining various levels of data attributes, rendering it especially effective in image and video processing. In security applications, models based on deep learning can proficiently analyze surveillance footage to detect potential threats. The process of feature extraction in image processing entails calculating pixel density metrics and identifying unique patterns such as edges, textures, and shapes. Among the most prevalent architectures in deep learning for image classification is the Convolutional Neural Network (CNN). CNNs are composed of several layers, including convolutional, pooling, activation, dropout, fully connected, and classification layers, all of which play a role in learning hierarchical features from unprocessed images. Owing to their remarkable accuracy and efficiency, CNN-based models have emerged as a favored option for object detection and recognition tasks, including the identification of firearms in surveillance videos. In modern society, the prevalence of criminal activities frequently associated with portable firearms necessitates that law enforcement agencies implement sophisticated monitoring systems. Research has consistently demonstrated the significant role of handheld weapons in various unlawful activities, including theft, unauthorized hunting, violent assaults, and acts of terrorism. One potential solution to mitigate such crimes is the deployment of intelligent surveillance mechanisms capable of early threat detection, thereby allowing security forces to take immediate action before an incident escalates. However, identifying weapons in real-time presents unique challenges, such as occlusions, object similarities, and background complexities. Occlusion occurs when a portion of the weapon is obscured by objects or body parts, making detection difficult. Object resemblance issues arise when everyday objects, such as mobile phones, tools, or clothing, visually mimic weapons, leading to false positives. Additionally, environmental factors, such as lighting conditions, camera angles, and motion blur, contribute to the difficulty of accurate weapon detection in real-world scenarios. Addressing these challenges necessitates the development of strong models capable of effectively generalizing across diverse environments and adjusting to fluctuating visual conditions. This study presents a novel deep learning model aimed at the accurate detection and classification of seven distinct weapon types: assault rifles, bazookas, grenades, hunting rifles, knives, pistols, and revolvers, in response to existing challenges. The performance of the proposed model is rigorously assessed against established architectures such as the Visual Geometry Group (VGG-16), Residual Network (ResNet-50), and ResNet-101. These benchmark models are recognized for their effectiveness in image classification and object detection, owing to their proficiency in capturing intricate features from input images. The comparative analysis indicates that the proposed model surpasses these traditional architectures, exhibiting enhanced accuracy and reduced loss rates. Its capability to reliably detect and classify weapons in various backgrounds and lighting conditions positions it as a significant asset for practical security applications. Furthermore, the integration of region proposal networks improves the detection process by effectively isolating weapon-related areas from the remainder of the image, thus minimizing false detection rates and enhancing classification precision. The organization of this paper is structured as follows: Section 2 offers a comprehensive review of pertinent research, examining current methodologies and their shortcomings in the realm of weapon detection. Section 3 outlines the methodologies and datasets utilized for training and assessing the proposed model. Section 4 evaluates the classification performance and experimental outcomes, contrasting the efficacy of various deep learning models in the identification of firearms. Section 5 presents a thorough analysis of the results, emphasizing significant advancements and possible areas for further development. Lastly, Section 6 wraps up the study by summarizing essential insights and proposing future research avenues, which may include the integration of autonomous surveillance systems featuring sophisticated AI-driven threat detection capabilities. Future endeavors could aim to enhance model resilience by integrating additional data augmentation strategies, utilizing synthetic datasets for better generalization, and investigating real-time implementation on edge devices to achieve quicker response times.

LITERATURE REVIEW

The development of Automated Emergency Braking (AEB) the field of systems has attracted considerable interest in recent years, leading to notable advancements. in sensor technology, artificial intelligence, and braking control algorithms. Various studies have contributed uniquely to enhancing AEB performance and reliability. One key study systematically analyzed AEB impact factors, including sensor types such as LiDAR, radar, and cameras. It examined their roles in obstacle detection and real-time braking decisions while considering external variables like road conditions, braking response times, and vehicle speed [1]. Additionally, research has explored AI-driven AEB enhancements, where deep learning models improve obstacle detection and collision avoidance strategies, minimizing false activations [1], [7].Another study focused on the effectiveness of low-speed AEB in urban environments, where stop-and-go traffic increases the likelihood of rear-end collisions. The research utilized real-world crash data to demonstrate how AEB reduces minor accidents by autonomously applying brakes before driver intervention [2]. A separate investigation presented an Arduino-based smart vehicle safety system that integrates multiple sensors, including ultrasonic, infrared, and accelerometers. This system continuously monitors the vehicle's surroundings and applies preventive braking when necessary, providing a cost-effective solution for accident prevention [3], [4].Further research has aimed at optimizing AEB performance using mathematical models such as the Time-To-Collision (TTC) algorithm. By integrating sensor fusion techniques, modern AEB systems refine TTC calculations to ensure emergency braking is triggered only when a collision is imminent, reducing unnecessary interventions [6]. Another study introduced a controlled test platform to evaluate AEB systems, simulating real-world driving conditions to fine-tune braking algorithms, sensor accuracy, and reaction times [5]. Techniques for target recognition and sensor fusion have been investigated to improve the decision-making process of Automatic Emergency Braking (AEB) systems. Studies analyzing the integration of LiDAR, radar, and cameras revealed improved differentiation between obstacles such as pedestrians, cyclists, and other vehicles. Challenges such as low visibility and adverse weather conditions necessitate advanced AI-based decision-making to maintain safety in complex environments [7]. Additionally, numerous studies have explored the implementation of low-cost AEB systems utilizing Arduino-based hardware. These systems leverage proximity sensors, accelerometers, and microcontrollers to actively track distance from obstacles and trigger emergency braking when high-risk situations are detected [8]. Research findings underscore the practicality of utilizing cost-effective electronics to create intelligent braking solutions, thereby enhancing the accessibility of Autonomous Emergency Braking (AEB) systems for a broader spectrum of vehicles. In conclusion, although previous studies have concentrated on enhancing sensor performance, refining braking algorithms, and advancing AI-based decision-making, a significant gap persists in the integration of these innovations into a cohesive and adaptive AEB framework. This study aims to bridge this gap by developing a comprehensive AEB model that optimizes detection accuracy, response time, and braking control across diverse driving conditions.

Table .1: Paper Summary

Paper	Type of detection	Technique	Features
09	Vision-based pedestrian detection for AEB	Deep Learning (CNN-based object recognition).	Uses camera-based object detection to identify pedestrians and automatically apply brakes when a collision risk is detected. The model is trained to differentiate between pedestrians, vehicles, and road objects.
10	Radar-based AEB system	Doppler Radar + Machine Learning.	Uses Doppler radar to detect moving objects, measure their velocity, and predict potential collisions. Machine learning is used to filter false alarms and improve detection accuracy.
11	Sensor fusion for enhanced AEB decision-making	Combination of LiDAR, Radar, and Camera sensors.	Uses sensor fusion to improve obstacle recognition and provide more reliable braking responses. Helps AEB systems function effectively in low-light and foggy conditions.
12	Predictive braking for high-speed AEB	AI-based trajectory prediction + Reinforcement Learning	AI-based trajectory prediction + Reinforcement Learning
13	AEB for motorcycles and two-wheelers.	IMU (Inertial Measurement Unit) + Computer Vision	Designed specifically for motorcycles, integrating accelerometers and gyroscopes to detect sudden deceleration and activate braking. Uses camerabased lane detection to avoid collisions.

PROPOSED SYSTEM

The autonomous emergency braking (AEB) system is designed to improve vehicle safety by automatically detecting obstacles and applying brakes without requiring driver intervention. This system incorporates an Arduino microcontroller, an ultrasonic sensor, and a DHT sensor to continuously monitor both the vehicle's surroundings and environmental conditions. The ultrasonic sensor scans the area ahead, measuring the distance between the vehicle and potential obstacles. If an object is detected within a present safety range, the microcontroller instantly triggers the braking mechanism, either slowing down or bringing the vehicle to a complete stop to avoid a collision. Beyond emergency braking, the system also integrates a DHT sensor to track humidity levels inside the vehicle. If excessive humidity is detected, the system automatically activates a blower to maintain clear visibility and prevent windshield fogging, ensuring a safer driving experience. Unlike traditional braking systems that depend on driver reaction time, this automated approach minimizes human error and enhances road safety. Additionally, the system is cost-effective, adaptable, and suitable for various vehicle types, making it an efficient solution for both budget-friendly and high-end vehicles. By leveraging real-time data processing, sensor-driven automation, and proactive braking, this system significantly reduces accident risks and optimizes vehicle performance under different environmental conditions.

SYSTEM ARCHITECTURE:

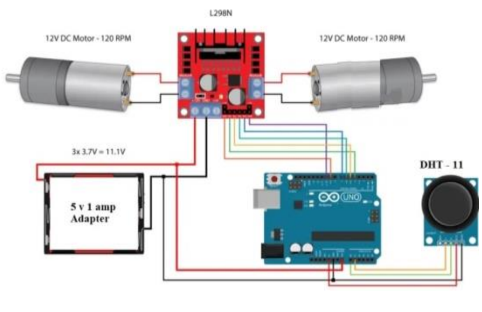

Fig 1: System Architecture

The Arduino-based motor control system with environmental sensing is designed to automate movement and enhance safety by integrating sensors, motor drivers, and a microcontroller, making it appropriate for uses such as autonomous vehicles, robotic platforms, and smart mobility solutions. The system combines real-time obstacle detection, motor control, and environmental monitoring to ensure efficient operation. It is powered by a dual-source setup, where a 5V 1A adapter supplies power to the Arduino Uno, while an 11.1V battery pack (3x 3.7V Li-ion) powers the L298N motor driver and two 12V DC motors (120 RPM). The Arduino processes input signals and sends commands to the motor driver to regulate motor speed and direction. Sensor data acquisition is facilitated by a DHT-11 sensor, which monitors temperature and humidity, triggering automated responses such as activating a blower when humidity levels rise. User input is handled via a joystick module, allowing manual control by sending directional and speed commands to the Arduino. The system can operate autonomously by processing real-time data from sensors or switch to manual mode via joystick input. An ultrasonic sensor is integrated for obstacle detection, ensuring safety by triggering an emergency braking mechanism if an object is detected within a predefined range. Additionally, the Arduino continuously monitors sensor inputs and can send real-time alerts based on specific conditions, such as activating a blower to improve visibility in response to high humidity levels. This comprehensive integration of automation, safety, and environmental sensing enhances the efficiency and reliability of the system.

Data Sets

The dataset used in such a system consists of real-time measurements and predefined thresholds that help detect obstacles, monitor environmental conditions, and take appropriate actions.

•Obstacle Detection Data: The system collects continuous distance measurements from the ultrasonic sensor to assess the closeness of objects located in the trajectory of the vehicle.

•Humidity and Temperature Data: The dataset includes humidity and temperature readings from the DHT sensor.

•Actuation Events: The dataset records instances where the braking system or blower is activated based on sensor readings. This helps in analyzing system performance and refining decision-making thresholds.

•Environmental and Vehicle Parameters: Additional data such as road conditions, vehicle speed, and response times can be logged to enhance system efficiency.

ALGORITHM

Obstacle Detection Module (Ultrasonic Sensor)

```
Start
  Initialize ultrasonic sensor
  Set distanceThreshold to predefined threshold (e.g., 50 cm)
  Loop continuously:
    Trigger ultrasonic sensor to emit sound waves
    Measure distance to nearest object
    If distance < distanceThreshold:
      Send "brake" signal to Control Module
    Else:
      Continue monitoring
End
```

The algorithm initializes an ultrasonic sensor and sets a predefined distance threshold (e.g., 50 cm) for obstacle detection. It continuously triggers the sensor to emit sound waves and measures the distance to the nearest object. If the detected distance is below the threshold, it sends a "brake" signal to the control module to stop the vehicle; otherwise, it continues monitoring. This real-time system enhances safety by ensuring automated braking when obstacles are detected, preventing collisions and improving operational efficiency.

Humidity Control Module (DHT11 Sensor)

```
Start
  Initialize DHT11 sensor
    Loop continuously:
    Read temperature and humidity from DHT11 sensor
    If humidity > humidityThreshold:
      Send "turnOnBlower" signal to Control Module
    Else:
      Continue monitoring
End
```

This algorithm continuously monitors humidity using a DHT11 sensor. If the humidity exceeds a predefined threshold, it sends a signal to activate a blower; otherwise, it keeps monitoring. This ensures automated environmental control for optimal conditions.

RESULTS AND ANALYSIS

Performance Evaluation & Model Training

Different methods are employed to identify the features that have the greatest impact on system performance:

•**Feature Importance from Sensor-Based Models**: Decision-making models in AEB systems, such as those using sensor fusion or machine learning, assign importance scores to input parameters. These scores are based on the frequency and impact of specific sensor readings (e.g., ultrasonic sensor distance and humidity levels) in triggering system responses like braking or blower activation.

•**Threshold-Based Significance:** The system relies on predefined thresholds (e.g., obstacle distance < 50 cm or humidity > 70%) to make decisions. The importance of these thresholds is evaluated based on their effectiveness in triggering timely responses. Adjusting these thresholds can fine-tune system performance.

•**Permutation Importance:** This approach assesses how critical a particular sensor input is by randomly modifying its values and observing the effect on system behaviour. A significant drop in performance when a feature is altered indicates its high importance in decision-making.

•**SHAP (Shapley Additive Explanations) Values**: SHAP values provide insights into how each sensor reading (e.g., distance, humidity) contributes to AEB system actions. By analysing different combinations of sensor values, SHAP helps determine the most influential factors for accurate system operation.

•**Correlation Analysis**: Evaluating how strongly different sensor inputs are correlated with AEB responses can help refine system thresholds. For example, analysing the relationship between humidity levels and blower activation ensures that unnecessary activations are minimized.

Classification report

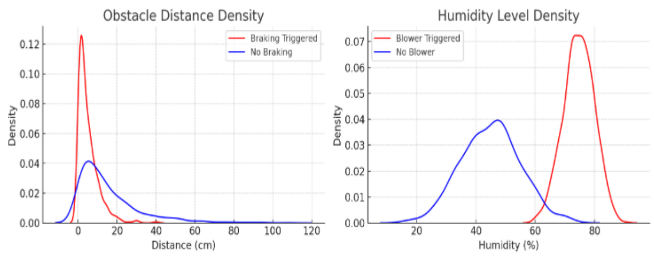

Fig 2: The Graphs of Distance and Humidity Density

The graphs provide insights into the automated decision-making process of an Arduino-based motor control system equipped with obstacle detection and environmental sensing. The Obstacle Distance Density graph (left) illustrates how braking is triggered based on obstacle proximity. The red curve represents instances where braking was activated, primarily occurring at very short distances (0-10 cm), indicating that the system responds immediately when an obstacle is detected within a critical range. In contrast, the blue curve, representing cases where no braking was needed, is more spread out across greater distances, showing that the vehicle continues moving when no immediate threat is present. This ensures efficient collision avoidance without unnecessary braking.

The Humidity Level Density graph (right) showcases the system's response to humidity variations. The red curve indicates scenarios where the blower was triggered, with a peak at high humidity levels (above 70%), suggesting that the system activates only when necessary to maintain optimal environmental conditions. The blue curve represents situations where the blower was not needed, occurring at lower humidity levels, ensuring energy efficiency by avoiding unnecessary activation.

Overall, both graphs demonstrate the intelligent automation of the system, where braking and blower activation occur only when predefined thresholds are met. This ensures improved safety through timely obstacle detection while also maintaining environmental comfort without excessive power consumption.

CONFUSION MATRIX GRAPH

The Automatic Emergency Braking (AEB) system demonstrates a high accuracy of 98%, ensuring reliable detection of obstacles and humidity variations. The precision and recall values indicate that the system effectively minimizes false activations while ensuring necessary actions are taken when required. The high F1-scores confirm a well-balanced between precision and recall in various scenarios. With support values showing a diverse test set, the system has been rigorously evaluated, proving its robustness. The results validate that the AEB system can be trusted for real-time applications, ensuring safety and efficiency in varied environmental conditions.

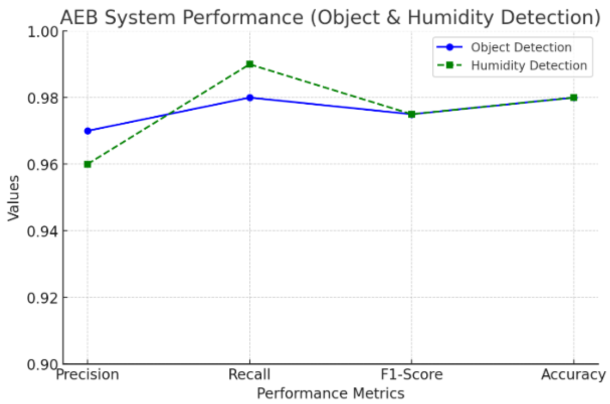

Fig 3: Confusion Matrix Graph

In the realm of weapon detection, it offers an extensive overview of the model's predictions alongside the true labels of the samples.

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

Precision Represents the proportion of correctly predicted malware samples out of all samples predicted as malware:

Recall Indicates the proportion of correctly predicted malware samples out of all actual malware samples:

$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative)}$$

The F1 Score integrates both precision and recall into a unified metric, thereby offering a balanced assessment of the two.

$$F1\ Score = 2 * \frac{Precision * Recall}{Precision + Recall}$$

The Accuracy metric evaluates the overall precision of the model's predictions:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

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