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Procedia Computer Science 00 (2025) 000–000

Procedia Computer Science

www.elsevier.com/locate/procedia

International Conference on Machine Learning and Data Engineering

Weapon Detection System using Deep Learning for Enhanced Performance across Varied Weather Conditions.

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Abstract

The creation of cutting-edge technologies for quick and precise firearm identification has become essential in response to the growing risks to global security. In situations where weapons may be partially hidden or camouflaged, this paper not only discusses the difficulties associated with weapon detection in dynamic and complicated real-world contexts, but also suggests enhancing its accuracy. Due to their inability to distinguish between weapons and non-threatening objects, traditional detection technologies frequently have high false-negative rates. This paper suggests using a Convolutional Neural Network (CNN) model that was trained on a wide range of datasets, comprising 88 categories of both weapons and non-weapons. Our methodology consists of an extensive pipeline for data augmentation and preprocessing intended to improve the robustness of the model.

Keywords: Weapon Detection, Convolutional Neural Network, Image Preprocessing, Deep Learning, Machine Learning

1. Introduction

Public safety has emerged as a crucial concern for communities, organizations, and governments alike in an increasingly linked world. The necessity for strong security measures has increased due to the growing threat of violence in public areas, whether from terrorist attacks, mass shootings, or other violent crimes. Because these places are frequently the focus of such threats, ensuring people's safety in crowded spaces like airports, schools, and public transportation systems has become extremely important. Globally, violent crime has increased significantly over the past few decades. An alarming rise in criminal activity has been attributed to the ease of access to weapons and the rising prevalence of weapon-related violence. With disastrous results, weapons, especially firearms have emerged as the preferred instrument of choice in numerous violent crimes. The employment of explosives, weapons, and knives not only makes attacks more deadly but also makes it more difficult for conventional security systems to effectively stop these kinds of events. The severity and regularity of these events have highlighted the critical need

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for improved early warning and surveillance systems that can spot possible threats before they materialize into full-fledged attacks. Preventing prospective attacks and reducing the loss of life and property depend heavily on the capacity to identify these weapons before they are utilized.

Some of the most serious and terrible crimes in recent memory, such as armed attacks and mass shootings, have been caused by the improper use of firearms in public areas. Not only have these tragic occurrences taken countless lives, but they have also caused widespread fear and panic. By promptly recognising weapons or questionable activities, effective detection systems can avert such catastrophes and enable prompt intervention and response. Their placement in public areas serves to calm people down and guarantees that law enforcement can respond quickly to reduce dangers, with the ultimate goal of averting violence before it happens. Crime prevention, especially weapon-related attacks, necessitates a proactive strategy that combines cutting-edge technology with advanced security measures. This technique relies heavily on early detection since it allows law enforcement and security experts to react to possible dangers quickly and efficiently. Modern technology, such sophisticated weapon identification algorithms and real-time monitoring tools, can be integrated into surveillance systems to improve the capacity to detect and evaluate threats before they escalate to something serious. By offering a thorough defensive system against possible incidents, this strategy not only strengthens public safety generally but also lowers the risk of assaults.

The majority of today's weapon detection systems rely on manual monitoring and simple object detection methods. Although considerable effectiveness has been achieved with these strategies, they are often limited in important ways. Manual monitoring is prone to human mistake and weariness, While basic object detection or basic weapon detection frequently struggles to effectively identify concealed or partially visible weapons . This difficulty is especially noticeable in busy, complicated environments where different viewpoints and the presence of several items could cover up possible dangers. Traditional models face additional challenges because of a wide range in weapon appearance, which includes variations in dimensions, forms, and designs. This diversity makes it more difficult to discern between innocuous objects and real dangers, which could result in false negatives and decreased accuracy overall.

This research proposes a Convolutional Neural Network (CNN)-based model specifically made for weapon detection even in resilient weather situations in order to address these limitations. With the help of deep learning, our model is able to interpret visual input more thoroughly. This allows it to accurately identify a wide variety of weapons, even ones that are hidden or only partially visible. Our CNN-based model is designed to precisely solve the shortcomings of current weapon identification systems by utilizing cutting edge feature extraction methods that can distinguish even the smallest differences in weapon appearance. This method improves the model's versatility and accuracy in a variety of settings and situations. By integrating this, detection performance can be improved in dynamic and complicated situations, leading to a notable improvement in the ability to distinguish between real dangers and non-threatening objects. By addressing the shortcomings of conventional detection systems, this strategy seeks to offer a more dependable and efficient means of protecting public areas.Our CNN-based approach offers numerous significant enhancements over conventional detection techniques. First off, because of its deep learning architecture, which enables it to identify intricate patterns in visual data, it offers better accuracy in weapon detection. Second, because the model can operate in real-time, dangers are identified early on rather than after the fact.

Finally, the model is a dependable tool for a variety of security applications since it is more resistant to changes in weapon look and environmental factors. With these improvements, our model becomes an essential part of contemporary surveillance systems, greatly increasing their effectiveness in maintaining public safety.

2. Related Work

Several research studies have explored various approaches to firearm detection using advanced machine learning and deep learning techniques, achieving significant success in enhancing accuracy and reliability. Khalid et al(1) demonstrated the effectiveness of real-time weapon detection models in improving public safety and assisting law enforcement agencies using algorithmic deep learning techniques to identify weapons early. Similarly, Mehta et al.(2) developed a deep learning-based model using the Darknet53 framework, showing remarkable accuracy in detecting guns and fire anomalies in real-time surveillance, highlighting the model's efficiency on GPU-based systems.

Tiwari et al.(3) suggested a technique for visual firearm detection using segmentation based on color and SURF features, which proved resilient against affine variations and occlusions, allowing the identification of multiple firearms within a single image. Egiazarov et al.(4) presented a novel approach by employing an ensemble of neural networks, each focused on different aspects of weapon features, demonstrating robustness across various data types, including synthetic and out-of-sample video frames.

Further, Castillo et al.(5) presented a technique for automatic detection of cold steel weapons, utilizing a luminosity-based preprocessing technique, which showed exceptional performance even in low-quality videos, making real-time applications appropriate for it. Grega et al.(6) developed algorithms specifically designed for detecting firearms and knives in low-quality CCTV footage, with the knife detection algorithm achieving higher sensitivity compared to firearm detection, indicating potential for integration into real-time surveillance systems.

Verma et al.(7) conducted extensive assessments of weapon detection systems under challenging conditions, finding that the Support Vector Machine (SVM) classifier outperformed others with a high classification accuracy, demonstrating the system's potential for real-time visual handheld gun detection. Additionally, Krishna Asrith et al.(8) combined Haar cascades with convolutional neural networks for weapon detection, which proved highly effective for real-time applications, especially in low-resolution imagery.

Moreover, the Faster R-CNN algorithm has been shown to outperform other models such as SSD in terms of accuracy and detection speed, as highlighted by Jain et al.(9), making it a strong candidate for real-time weapon detection. Similarly, Sagar et al.(10) emphasized the computational efficiency and detection accuracy of Faster R-CNN in recognizing firearms, further supporting its application in smart surveillance systems.

Finally, Ashraf et al.(11) demonstrated the efficacy of the YOLOv5s model in detecting handguns, achieving high precision and recall rates in real-time scenarios, while Bhatti et al.(12) showcased the YOLOv4 model's performance in real-time CCTV surveillance, significantly reducing false positives and negatives, and achieving high mean average precision. Barath et al.(13) proposed automatic weapon identification system aimed at improving real-time security and safety management, particularly in regions affected by violence, with potential economic benefits by attracting safety-conscious investors and tourists. Tiwari et al.(14) proposed a color-based segmentation and Harris interest point with FREAK descriptors-based gun detection algorithm. The technique handles differences like occlusion and scale and detects weapons by comparing segmented objects to a gun descriptor. Santos et al.(15) review Deep Learning techniques for weapon detection, emphasizing the transition from two-step models like Faster R-CNN to single-stage models like YOLO. While these models are versatile, they face performance challenges in difficult conditions. These works collectively underscore the advancements in weapon detection technologies, contributing to improved security and safety measures across various applications.

There are still a number of issues with weapon detection systems, especially with deep learning models' bulkiness, computational inefficiencies, and inconsistent detection performance in various contexts, despite the significant advancements in the field as reported in the works referenced. Although many of the current models are powerful, real-time application is hampered by high computational needs, particularly when using conventional hardware, by models like SSD and Faster R-CNN. Further problems these models frequently encounter are false positives and negatives, especially in low-quality footage or when handling lighting and occlusion fluctuations.

By maximising the trade-offs between operational effectiveness and model complexity, our system pushes the limits of existing technologies and delivers a reliable tool for improving public safety while also offering a more scalable and workable real-time weapon detection solution.

3. Proposed Work

A custom dataset including 5,000 images from 88 distinct categories was employed in this work.

The dataset partitioning is shown in Figure 1, where it is split into three subsets: 10% for testing, 10% for validation, and 80% for training. 4,000 photos were used in total.

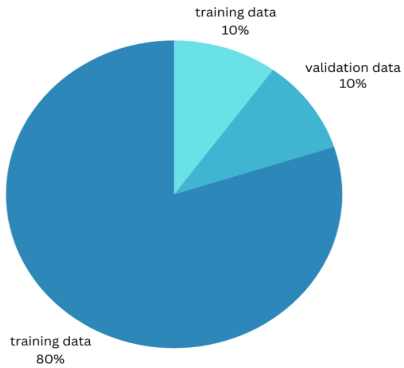

Fig. 1. Dataset Partitioning

Here is how the dataset is divided into categories for weapons and non-weapons:

The weapon categories include Pistols, Revolvers, Knives, Machetes, Daggers, Hatchets, Battle Axes, Hand Grenades, Flashbangs, Bombs, Molotov Cocktails, Katana, Sabre, Throwing Knives, Bayonets, Kukri, Tomahawks, Revolver Shotguns, Machine Pistols, Smoke Grenades, Stun Grenades, Chemical Bombs, Thermite Charges, Crossbows, Slingshots, Blowguns, Batons, Pepper Spray, and Tasers etc.

The non-weapon categories include Hammers, Screwdrivers, Wrenches, Pliers, Saws, Drills, Crowbars, Kitchen Knives, Scissors, Box Cutters, Forks, Spoons, Gardening Tools, Pens, Pencils, Rulers, Nail Clippers, Toy Guns, Toy Swords, Toy Knives, Plastic Tools, Action Figures, Toy Grenades, Toy Axes, Baseball Bats, Hockey Sticks, Golf Clubs, Archery Bows, Fishing Knives, Fencing Swords, Remote Controls, Smartphones, Laptops, Tablets, Flashlights, Power Banks, Headphones, Umbrellas, Walking Canes, Camera Tripods, Flash Drives, Sunglasses, Wallets, Keychains, Car Keys, Water Bottles, Pipes, Bolts, Tape Measures, Spirit Levels, Chains, and Construction Helmets.

A thorough selection of weapon photos taken from the sample dataset is shown in Figure 2. A variety of weapon kinds and modifications are displayed in this visual depiction, which sheds light on the complexity and diversity of the training and evaluation dataset.

Fig. 2. Sample Weapon Images from taken Dataset

3.1 Preprocessing Techniques Applied to the Datasets

A number of preprocessing methods were used to make sure that the dataset photos were uniform in size, orientation, and color space before our deep learning model was trained. To increase the model's resilience and generalizability, preprocessing procedures included resizing, rescaling, and image augmentation. The following is a breakdown of these methods:

- **Resizing and Rescaling**: Each image in the collection was adjusted to have a constant 360 by 360 pixel size. This resizing process guarantees that the model's input size is constant. To rescale the images to the interval [0, 1], the pixel values were likewise divided by 255.. The neural network's training stability and performance depend on the input data being normalized, which is made possible by this rescaling.
- **Data Augmentation**: Several techniques for data augmentation were applied in order enhance the model's potential to manage various visual cases and generalize:
  - **Random Flipping**: Images were randomly flipped both horizontally and vertically to introduce variability in image orientation.
  - **Random Rotation**: Images were rotated randomly by up to 72 degrees to simulate different viewing angles.
  - **Random Zoom**: Random zooms of up to 20% were applied to introduce variability in object scales.
  - **Random Contrast**: Contrast of the images was randomly adjusted by up to 20% to account for varying lighting conditions.
  - **Random Brightness**: Brightness was randomly adjusted by up to 20% to simulate different lighting conditions.
  - **Random Translation**: Images were translated randomly by up to 10% of the width and height to account for different object positions.

3.2 Proposed Method for Weapon Detection

We used a Convolutional Neural Network (CNN) model that is intended to classify and identify different sorts of weapons from photographs for our weapon identification challenge. Our CNN model's architecture and methods are organized as follows:

Model Architecture:

Our CNN model consists of five convolutional layers, with pooling layers in the middle and fully connected dense layers at the very end.
The following is the precise architecture:

- **Convolutional Layers:**
  - **Layer 1:** 32 filters of size 3x3.
  - **Layer 2:** 64 filters of size 3x3.
  - **Layer 3:** 128 filters of size 3x3.
  - **Layer 4:** 256 filters of size 3x3.
  - **Layer 5:** 512 filters of size 3x3.

Figure 3 illustrates the activation function of the Rectified Linear Unit (ReLU). This function, with a stride of 1, is employed throughout all of the previously mentioned layers and plays an important part in the model's non-linearity, which is required for neural network performance and learning. The picture demonstrates ReLU's essential qualities, including its nonlinear behavior and contribution to improving the model's capacity to learn complex patterns.

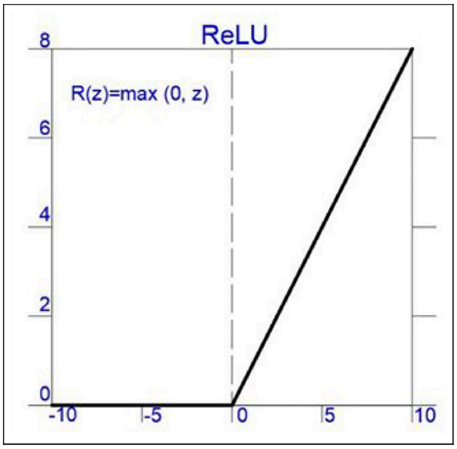

Fig. 3. Rectified Linear Unit (ReLU)

- **Pooling Layers:**
  - Max pooling layers with a pool size of 2x2 are applied after each convolutional layer to reduce spatial dimensions by a factor of 2, effectively halving the width and height of the feature maps.
- **Flattening and Dense Layers:**
  - **Flatten Layer:** Develops 1D vectors from 3D feature maps.
  - **Dense Layer 1:** 128 units in a fully connected layer with ReLU activation.
  - **Dense Layer 2:** The output layer consists of 88 units (one for each class) and uses a softmax activation function to generate class probabilities.

Data Preprocessing and Augmentation:

Data preprocessing and augmentation are essential procedures in getting the dataset ready for training. They include scaling, normalization, and random transformations, among other things, to enhance the model to a wide variety of data changes and improve generalization and resilience. Preprocessing and augmentation methods such as the following were used to improve model resilience and performance:

- **Resizing and Rescaling:**
  - Images were resized to 360 x 360 pixels to ensure a uniform input size.
  - The pixel values were adjusted as previously described in Section 3.1.
- **Data Augmentation:**
  - Random horizontal and vertical flips with a probability of 0.5.
  - Random rotations up to 20 degrees.
  - Random zoom with a spread of 20%.
  - Random contrast modification with a spread of 20%.
  - Random brightness modification with a spread of 20%.
  - Random translations up to 10% of the image height and width.

Training Procedure:

- **Model Compilation:**
  - With a learning rate of 0.001, the Adam optimiser was used to train the model.
  - SparseCategoricalCrossentropy was used as the function of loss.
  - Accuracy was chosen as the evaluation metric.
- **Training:**
  - Using a batch size of 32 and 100 epochs as the loss function, the model was trained.
  - During training, the dataset was shuffled with a buffer size of 1,000 and prefetched to optimize processing speed.

Evaluation:

- Following training, 500 photos from the test dataset were used to assess the model. Performance measures, such as accuracy and loss, were calculated to evaluate how well the model classified the 88 different types of weapons.

Deployment:

- For usage and deployment in the future, the trained CNN model was stored in a.keras file. This model provides useful insights and precise classifications based on real-time picture data, making it suitable for use in real-time weapon detection applications.

The entire model's workflow is shown in Figure 4, which shows each step of the procedure from data input to feature extraction, classification, and final prediction, as well as preprocessing and augmentation. This thorough diagram gives a clear picture of the model's operational structure and methods by highlighting how the model handles and changes data at each stage.

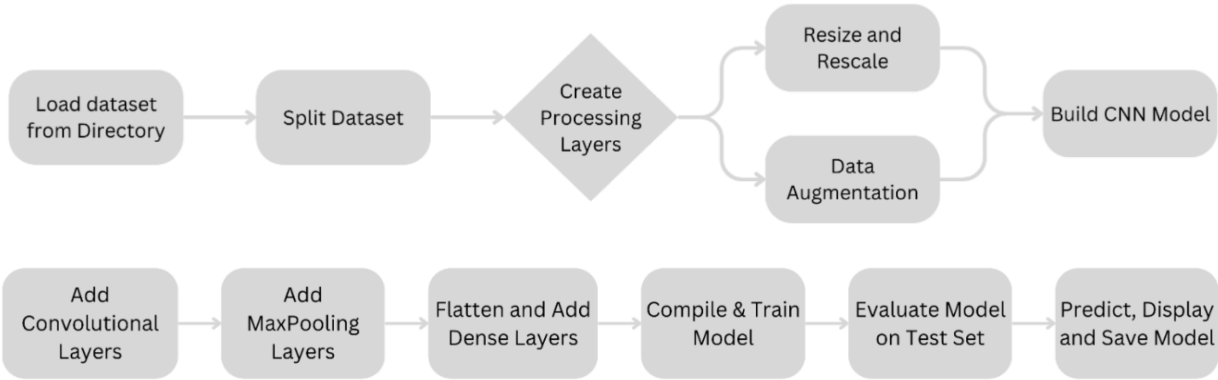

Fig. 4. Entire model's workflow

4. Result

Ultimately, we have produced a trained CNN model that surveillance systems can employ to identify weapons. It provides class probabilities and can detect weapons in photos with high accuracy. With an 85% accuracy rate on the test set, the model is deemed reliable for use in practical scenarios. Preprocessing and data augmentation methods are used to modify the model in order to optimize it for certain use scenarios, such as weapon recognition in a variety of environmental conditions (fog, bad illumination, and different angles). It can adjust to a variety of real-world monitoring scenarios because to its versatility.

Utilizing data augmentation methods like random flips, rotations, zooms, and brightness adjustments strengthens the model and makes it capable of handling a large range of input image variations. Because of this, the model performs well in real-world applications and is less prone to malfunction in various scenarios, such as those with changing lighting, angles, or resolutions. Furthermore, in circumstances where a variety of weapon kinds may be present, the model is a great option for weapon identification because it can distinguish between 88 different categories. It guarantees excellent performance even with a wide range of input while retaining accuracy across different kinds of weaponry.

Figure 5 shows how this model would categorize different things in the picture and give each prediction a confidence value (e.g., a gun with a 92% confidence score may be identified). When an object is detected as a weapon, the model is quite certain about it, as shown by a high confidence score; a lower confidence score shows less conviction. Practically speaking, the confidence score aids in deciding whether to respond in response to objects observed, particularly in real-time security or surveillance systems. An alert may be set off, for example, if the confidence score in identifying a weapon is higher than a predetermined threshold (such as 90%)

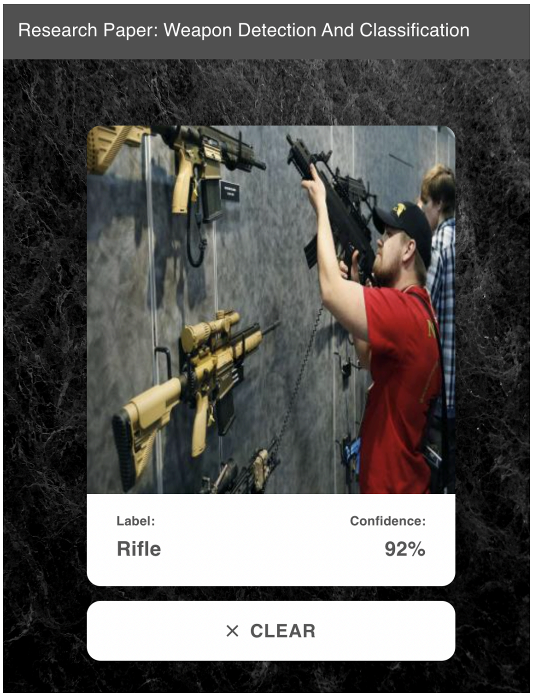

Fig. 5. Result showcasing weapon detection interface

5. Conclusion

In this paper, we suggested a Convolutional Neural Network (CNN)-based weapon detection model for surveillance systems to identify different types of firearms. With data augmentation approaches, the model can manage a variety of environmental situations, such as low lighting, fog, and different angles, and it shows an accuracy of 85% on the test set. With 88 different categories for weapon classification, it provides a dependable answer for practical uses. Nevertheless, the model still has issues with harsh lighting and demands for real-time processing. We believe there are many possible improvements, such as optimizing time and space complexity to implement real-time performance, which could be explored in future work.

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