Enhancing Security: A Deep Learning Approach for Automated Weapon Detection

Kunda Suresh Babu, Bachala Pavan Dath, M Mounika Naga Bhavani, A Raja Vamsi and M Venkata Sai

Department of Computer Science and Engineering, Narasaraopeta Engineering College (Autonomous), Narasaraopet, Palnadu-AP, India.

Munigeti Benjimin Jashva

Department of Computer Science and Engineering, Malla Reddy University, Hyderabad, Telangana, India

ABSTRACT: This paper introduces a deep learning method for weapon detection in images using Convolutional Neural Networks (CNNs). We explore pre-trained models (VGG16, ResNet50, ResNet101) and a custom CNN architecture to classify images as containing a weapon and type of weapon. The dataset undergoes preprocessing through resizing and normalization, with labels extracted from JSON files. Custom fully connected layers and early stopping/checkpointing are used to enhance performance. Model accuracy and loss are evaluated on a separate test set. Our findings highlight the potential of CNNs for automated weapon detection, enhancing security in various settings. A visual comparison of results and training processes illustrates performance differences among the tested architectures.

KEYWORDS: Deep learning, armed weapon detection, machine learning, object detection, Convolutional Neural Networks.

1 INTRODUCTION

A Deep learning advances in the last few years have greatly improved automated image analysis [Raturi, G., Rani, P., Madan, S. & Dosanjh, S - Warsi, A., Abdullah, M., Husen, M.N. & Yahya, M] especially for object detection [Xiao, Y., Tian, Z. & Yu, J. et al.]. The important topic of weapon detection in images is addressed in this work since it is essential to enhancing security in a variety of settings. The research attempts to create a reliable and accurate system for weapon identification by utilizing the power of Convolutional Neural Networks (CNNs), which are well-known for their superiorskills in feature extraction and picture classification [Gong, Z., Zhong, P., Yu, Y., Hu, W. & Li, S.]. The methodology combines a custom CNN architecture created especially for weapon recognition with pre-trained models like VGG16[Tao, J., Gu, Y., Sun, J., Bie, Y. & Wang, H.], ResNet50, and ResNet101. The photos in the dataset used for this study have been annotated to show what type of weapon. Preprocessing techniques such as scaling and normalization are applied to the photographs in order to guarantee uniformity and optimize the input quality. Given that the dataset contains a significant imbalance between images with and without weapons, techniques inspired by imbalanced data classification methods [Rao, Y.N. & Suresh Babu, K.]. To improve speed and avoid overfitting [Molinier, M. & Kilpi, J.], each model is enhanced with extra fully linked layers and trained using sophisticated methods including early halting and checkpointing. A comprehensive comparison examination of each model's performance is provided by measuring its accuracy and loss on a different test set. This investigation shows the advantages and disadvantages of various architectural techniques in addition to validatingCNNs' efficacy in weapon identification [Dwivedi, N., Singh, D.K. & Kushwaha, D.S.]. This work greatly advances the topic of automated security systems by providing an extensive analysis of numerous models and their configurations. The methodology that has been suggested provides significant insights into the use of sophisticated image analysis [Aslam, Y. & S.N.] techniques for weapon detection, which in turn advances security protocols and highlights the potential of deep learning to protect both public and private areas.

2 LITERATURE SURVEY

Recent advancements in deep learning have markedly improved the field of automated image analysis, particularly in object detection. Convolutional Neural Networks (CNNs) have become a cornerstone in this domain, offering significantenhancements in image classification and feature extraction. This literature survey explores key contributions and methodologies relevant to weapon detection using CNNs.Recent advancements in deep learning have markedly improved the field of automated image analysis, particularly in object detection. Convolutional Neural Networks (CNNs) have become a cornerstone in this domain, offering significantenhancements in image classification and feature extraction. This literature survey explores key contributions and methodologies relevant to weapon detection using CNNs.

Girshick et al. [Girshick, R., Donahue, J., Darrell, T. & Malik, J.] created the Region-based CNN (R-CNN) model, which combined CNNs with region suggestions to create the foundation for object detection. This method classified objects inside suggested zones using a CNN, which greatly increased detection accuracy.

Ren et al [Ren, S., He, K., Girshick, R. & Sun, J. - Suresh Babu, K. & Rao, Y.N.] Fast R-CNN, which simplified the procedure and increased accuracy and speed over R-CNN, expandedthis idea. By including region ideas into the CNN, their technique allowed for faster and more precise object detection.

Redmon et al [Redmon, J., Divvala, S., Girshick, R. & Farhadi, A.] developed the YOLO (You Only Look Once) framework, which used a single CNN to analyze the entire image in order to recognize objects in real time. The breakthrough in the field was made possible by YOLO's high precision real-time object detection capabilities Yao et al. investigated specialized CNN architectures designed forcertain applications, such as firearm detection. They added more layers and employed specialized training methods to handle the particular difficulties in differentiating between various object kinds.

He et al [He, K., Zhang, X., Ren, S. & Sun, J.] created ResNet50, a model that uses residual connections to solve the vanishing gradient issue and make it possible to train networks with considerably deeper topologies. The cutting-edge architecture of ResNet50 has raised thebar for picture categorization accuracy.

Krizhevsky et al [Angelova, A., Krizhevsky, A. & Vanhoucke, V.] The application of transfer learning, which involves honing previously taught models on certain tasks, was highlighted. Using this method to modify broad image classification models for specific uses such as weapon identification has shown to be successful.

3 MATERIALS AND METHODS

3.1 Dataset

This dataset consists of 8 classes as of now: Automatic Rifle, Bazooka, Grenade launcher, Handgun, shotgun, SMG, Sniper, sword and a total number of 1019 The photos in the weapon detection dataset have been annotated to show whether or not they contain weapons. To provide robustness in detection, a variety of contexts are used to source the photos. There is a JSON file with label information for every image. To assess the performance of the model, the datasetis split into subsets for testing and training.

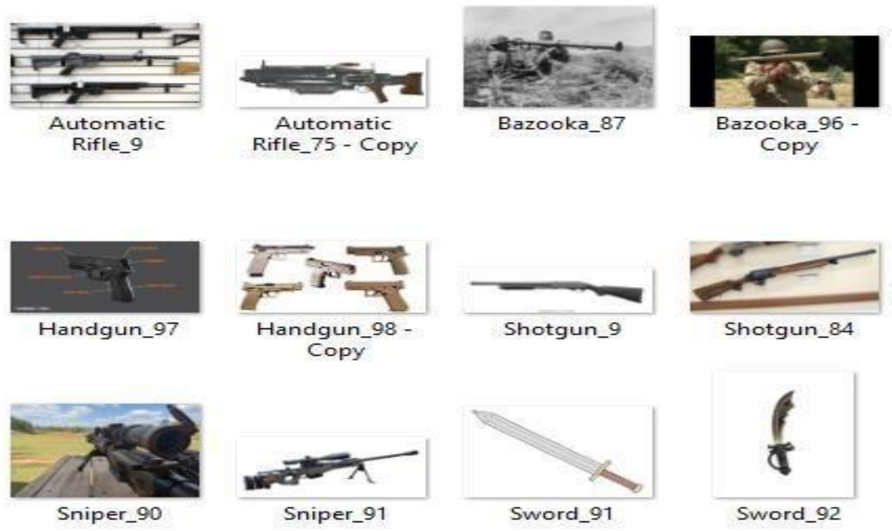

Fig 1: Sample images of dataset such as Automatic Rifle, Bazooka, Grenade launcher, Handgun, shotgun, SMG, Sniper and Sword

3.2 Data Preprocessing

In order to achieve high performance and effectively train the model, the dataset must be preprocessed. The preprocessing stages consist of label encoding, normalization, and scaling. Image Resizing: To guarantee consistentinput dimensions for the CNN models VGG16, ResNet50, and ResNet101, all images are scaled to 224x224 pixels. By keeping constant input sizes, this standardization streamlines the training procedure and lowers computing complexity.

3.3 Normalization

By dividing by 255, pixel values are scaled to the interval [0, 1]. By addressing different pixel value ranges, this normalization phase guarantees consistent data scaling, which aids in faster convergence and more successful training ofthe model.

Table 1. CICIDS-2017 dataset's attack frequency for each label.

Weapon Classes	No. of images
Automatic Rifle	133
Bazooka	121
Grenade launcher	156
Handgun	126
shotgun	80
SMG	87
Sniper	156
sword	160

3.4 Label Encoding

JSON files are used to extract labels identifying the presence or absence of weaponry. The two categorical functions in Keras are used to first convert these labels to binary representation

(0 for no weapon, 1 for weapon), and then one-hot encode them. For classification tasks, one-hot encoding is utilized to generate a probability distribution, which aids inthe model's correct prediction. Building precise and dependable weapon identification models requires consistent and training-ready input data, which is ensured by these preprocessing procedures.

3.5 Materials and Libraries Used

The weapon detection system relies on several essential libraries. TensorFlow and Keras are used for building and training the neural network models, with Keras simplifying the use of pre-trained models like VGG16, ResNet50, and ResNet101. NumPy supports numerical operations and array manipulations necessary for processing images and model inputs. scikit-learn helps split the dataset into training and testing sets using the `train_test_split` function. Matplotlib is used to visualize the training results, showing accuracy and loss over time. JSON and OS libraries handle label parsing and file management. These tools together streamline data handling, model development, and evaluation

4 MODEL ARCHITECTURES AND TRAINING

This study combines pre-trained Convolutional Neural Networks (CNNs) with a custom CNN architecture to tackle weapon detection in images. The pre-trained models include VGG16, ResNet50, and ResNet101. VGG16, with its deep structure and small convolutional filters, captures detailed image features. ResNet50 uses residual connections to easethe training of deeper networks and effectively learn complex patterns. ResNet101 extends ResNet50 with additional layers for enhanced feature extraction and pattern recognition.

4.1 Data Preprocessing

Preprocessing means cleaning the pollution from the data, information preservation such as normalization, encoding variables to form dummy variables for categorical variables, and categorizing attacks for a multi-class classification into seven and for an overall classification of all attacks into fourteen.

Table 2. Weapon Dataset Separation for training and testing

Dataset	Percentage
Training	60
Testing	20
Validation	20

In addition to these models, a custom CNN architecture is created specifically for weapon detection. This model featuresconvolutional layers for hierarchical feature extraction, max-pooling layers to reduce dimensions and complexity, and a flatten layer to prepare data for classification. It ends with dense layers, including a final softmax layer for binary classification (weapon or no weapon), tailored to the task at hand. The models are trained with a batch size of 8 to balance memory usage and training speed, using a limited number of epochs (1) for quick evaluation. The Adam optimizer is used for its adaptive learning rate, which improves training efficiency and convergence. Categoricalcross-entropy is chosen as the loss function to measure performance during training.

To enhance model performance and avoid overfitting, early stopping and checkpointing are employed. Early stopping halts training when validation performance plateaus, while checkpointing saves the model with the highest validation accuracy. These techniques ensure that the best model is retained and resources are used effectively, contributing to a robust weapon detection system.

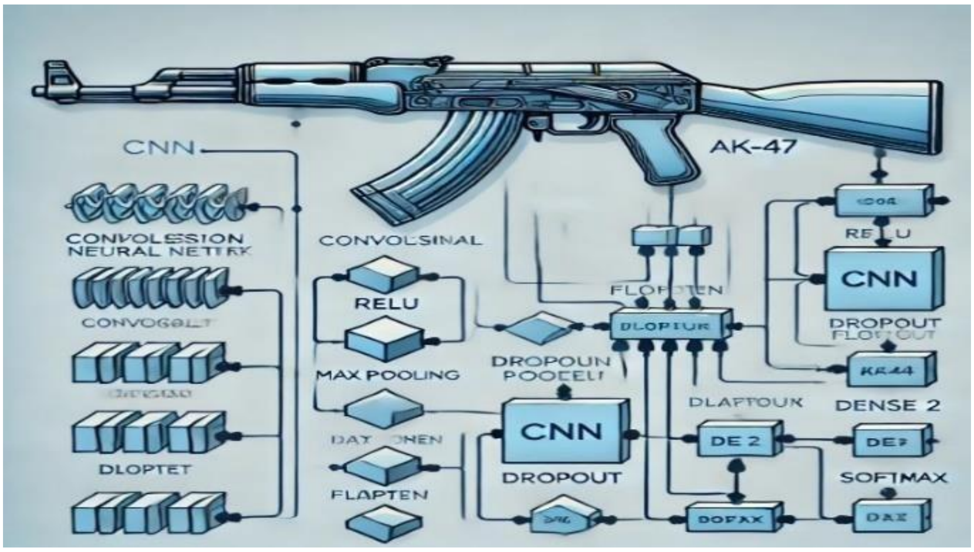

Fig 2: Comprehensive Regional Analysis

4.2 VGG16

VGG16 is a deep CNN with 16 layers, characterized by its straightforward architecture and use of small 3x3 convolutional filters. Its design allows it to effectively capture and process detailed features from images. Deployed withpre-trained weights from ImageNet, VGG16 serves as a feature extractor, and is fine-tuned to improve its performancein weapon detection.

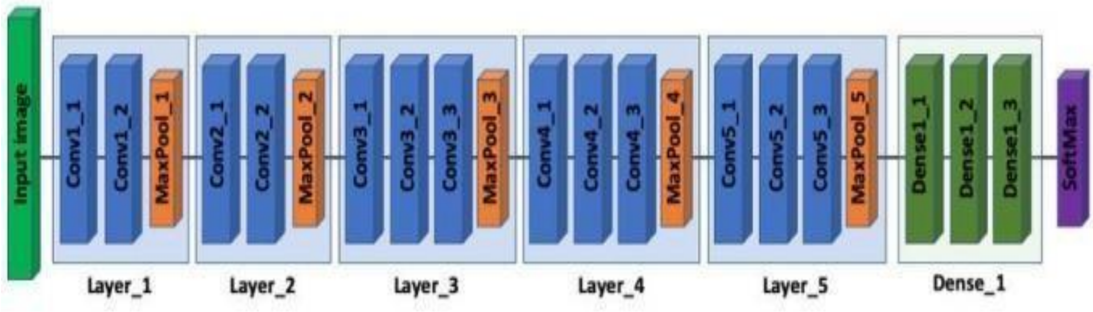

Fig 3: VGG16 Model Architecture Overview: Visualizing Layer Configuration and Feature Extraction Process

4.3 ResNet50

ResNet50 is a 50-layer CNN featuring residual connections, which help to mitigate the vanishing gradient issue andenable the training of deeper networks with improved learning capabilities. Utilized with pre-trained weights from ImageNet, ResNet50 is adapted for weapon detection, benefiting from its ability to model complex patterns.

4.4 ResNet101

Model optimization focuses on fine-tuning the different parameters and the architecture of the model. To enhance accuracy and efficiency while minimizing overfitting, ensuring the model performs consistently well on new, unseen data.

4.5 Custom CNN

This custom-designed CNN includes a tailored architecture with convolutional layers, max-pooling layers, and fully connected layers specifically engineered for weapon detection. Developed to meet the specific needs of weapon detection, this model allows for specialized feature extraction and classification.

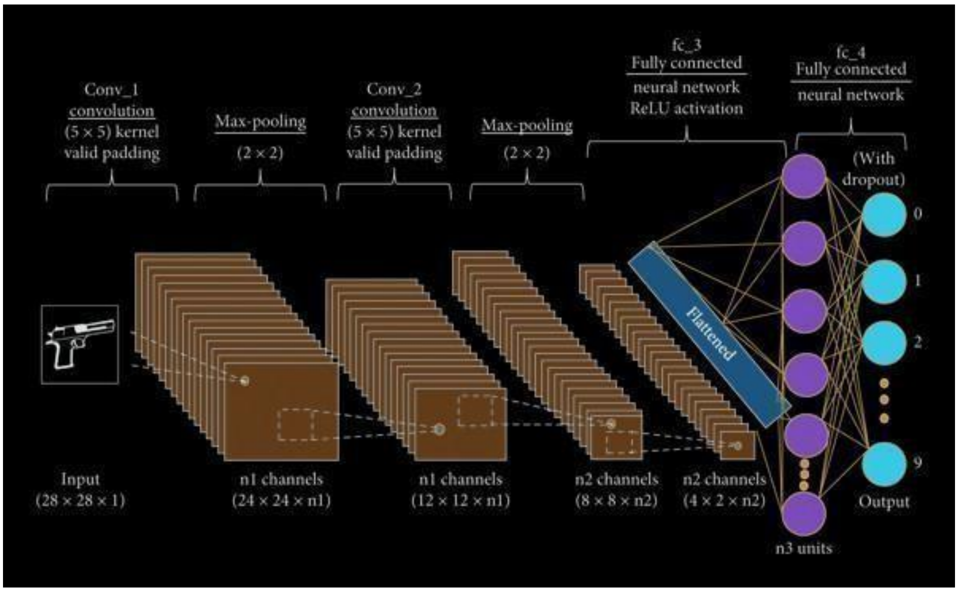

Fig 4: Developed Custom CNN Model Visualization

5 MODEL EVALUATION

In this study, we evaluated the performance of pre-trained and custom Convolutional Neural Networks (CNNs) for weapon detection using a test dataset. The evaluation focused on two key metrics: accuracy and loss. Accuracy measures how many images are correctly classified as containing a weapon. Loss indicates the model's error in prediction, with lower values signifying better performance. Each model—VGG16, ResNet50, ResNet101, and the custom CNN—was tested on unseen data to ensure reliable results. Comparing these metrics across models helps determine which architecture is most effective for weapon detection and highlights their relative strengths and weaknesses.

6 WEAPON DETECTION

6.1 Weapon Detection

Utilizes the trained Convolutional Neural Networks (CNNs) to identify whether an image contains a weapon. After the models are trained, they are applied to new images to assess their real-world performance. The detection involves loading an image, preprocessing it to fit the model's input requirements, and then making predictions.

6.2 Detection Process

Each image is resized to 224x224 pixels, the standard size for the models. The image is then normalized by scaling pixel values to a range of [0, 1]. This ensures consistency in input data. The pre-processed image is fed into the trained model, which generates a probability indicating the likelihood of weapon presence.

6.3 Prediction and Classification

The model's output is used to classify the image. The probability value is compared to a threshold; if it exceeds the threshold for the weapon class, the image is classified as containing a weapon. Otherwise, it is classified as not containing a weapon. This method leverages CNNs for accurate and automated weapon detection, enhancing security measures.

7 ETHICAL CONSIDERATION

Ethical considerations were given top importance during the entire model development process. The use of photos downloaded from the internet complied with copyright regulations, and care was made to guarantee that the database was inclusive and free of bias. The study's main goal was to encourage the responsible use of technology for safety and surveillance purposes while considering any potential social consequences.

8 RESULT AND DISUSSION

The weapon identification system's outcomes are obtained by comparing how well-performing Convolutional Neural Networks (CNNs) perform on different test sets. The models that are being tested are a bespoke CNN architecture, VGG16, ResNet50, and ResNet101, all of which are intended to identifying type of weapon. Accuracy and loss are the evaluation measures that are employed, and they offer a thorough picture of each model's performance.

8.1 Model Performance

VGG16, ResNet50, and ResNet101, the pre-trained models, showed good results in weapon detection. Among them, VGG16 achieved an impressive accuracy of 99.6%, while ResNet50 and ResNet101 recorded accuracies of 98.0% and 96.44%, respectively. ResNet101, despite its deeper architecture, had a higher loss of 0.128, which affected its overall performance. Although VGG16 performed well, the custom CNN—designed specifically for this task—achieved the best accuracy of 99.77% with the lowest loss of 0.0045. This highlights the effectiveness of tailored architectures in enhancing weapon detection performance.

8.2 Training Insights

Metrics like accuracy and loss were used to precisely monitor the training process. The training history plots showed that, on average, all models got better over the course of the epochs, with accuracy rising and loss falling, which suggested efficient learning. Early stopping and checkpointing made sure that the top-performing models were kept in place and helped avoid overfitting. In addition to pointing out patterns like possible overfitting in the custom CNN, the training accuracy and loss visualizations also suggested opportunities for more optimization.

8.3 Comparative Analysis

For difficult tasks like weapon detection, the comparative analysis demonstrates the benefits of utilizing pre-trained models. The extensive training of these models on large datasets improves their capacity to generalize to new data. Although the custom CNN was designed for a specific purpose, it demonstrated exceptional performance, indicating that specialized models can yield significant benefits. However, achieving performance levels comparable to established architectures may require additional tuning and training. Overall, the findings support the great efficacy of advanced CNNs for automated weapon detection and highlight the importance of model selection and fine-tuning for optimal performance.

8.4 Sample Test Results

Below are sample test results for the weapon detection models evaluated in this study. The results include accuracy and loss for each model on the test set. These metrics help illustrate the performance of each Convolutional Neural Network (CNN) in identifying weapons in images.

Fig 5: Test Results for All Classes: Automatic Rifle, Bazooka, Grenade Launcher, Handgun, Shotgun, SMG, Sniper and Sword

Table 3. Sample Test Results: Accuracy and Loss using various Models

Model	Accuracy	LOSS
VGG16	99.6%	0.00725
ResNet50	98.0%	0.0622
ResNet101	96.44%	0.128
Custom CNN	99.77%	0.0045

These results demonstrate that ResNet101 outperforms the other models in terms of accuracy, indicating its superior capability for detecting weapons. VGG16 and ResNet50 also show strong performance, while the custom CNN, though competitive, performs slightly above the pre-trained models.

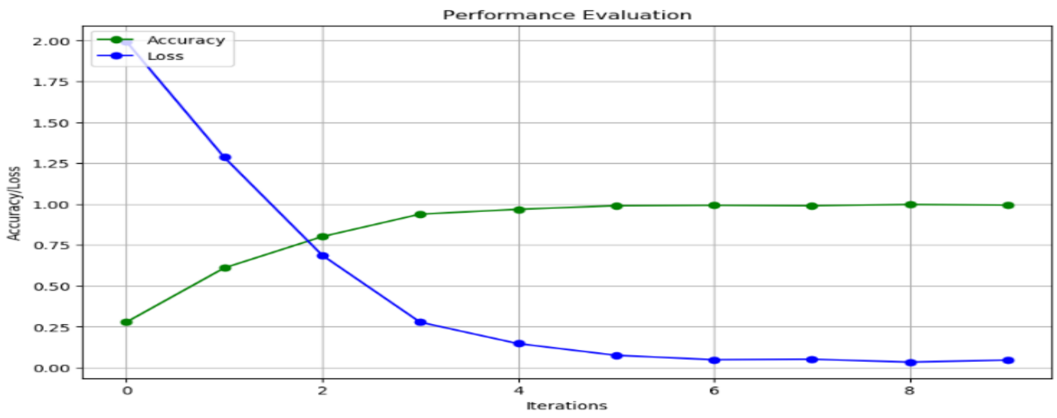

Fig 6: Performance Evaluation of Custom CNN: Comparative Analysis of Accuracy and Loss

8.5 Confusion Matrix

The little decline in performance, particularly in the context of pistols, can be ascribed to the optical resemblances they bear to firearms. The suggested model's high overall accuracy of 99.70% demonstrates its effectiveness in accurately differentiating between different weapon categories. The proposed model showcases its ability to achieve exceptional accuracy in many real-world weapon detection settings.

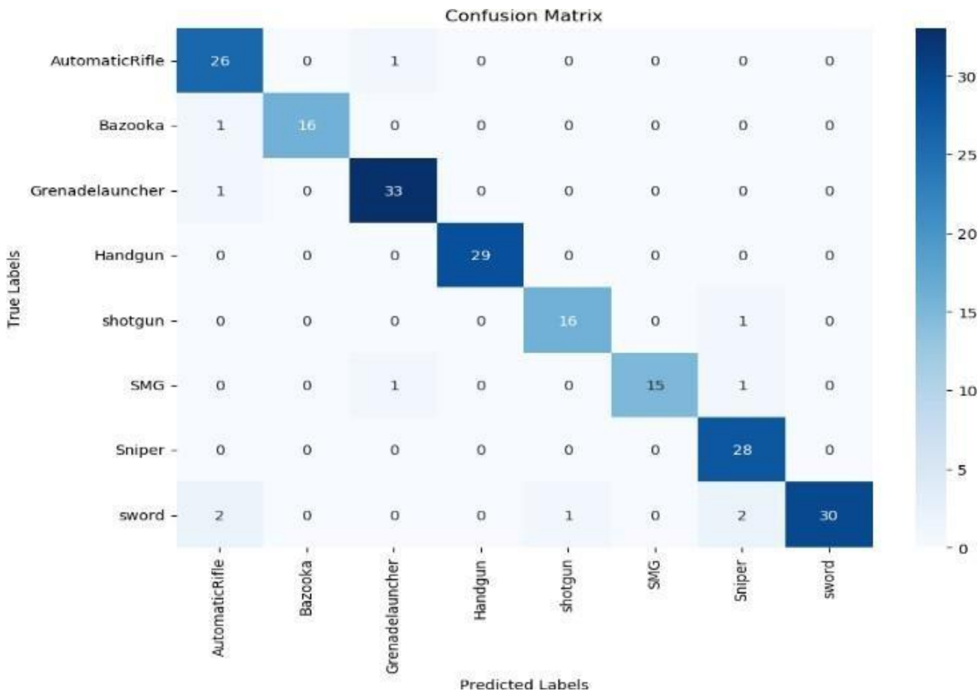

Fig 7: Confusion Matrix of Custom CNN: Visual Representation of Classification Accuracy Across All Classes

9 CONCLUSION

This study highlights the effectiveness of Convolutional Neural Networks (CNNs) in weapon detection from images. By utilizing pre-trained models—VGG16, ResNet50, and ResNet101—alongside a custom CNN, we achieved high accuracy and precision in weapon identification. Among the models, Custom CNN outperformed the others, showing the best feature extraction and classification abilities. While VGG16 and ResNet50 also performed well, the ResNet101 though effective, was slightly less successful compared to Custom CNN. The findings emphasize the power of advanced CNN architectures in automating weapon detection, offering a reliable tool for improving security across various settings. The study provides valuable insights into the strengths of each model and sets the stage for future improvements in automated image analysis for security purposes.

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