A Mini-Project Report On

Weaponry Detection using Artificial Intelligence for Security Applications

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Certificate

This is to certify that

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Of **M.Sc. (Data Science and Big Data Analytics)** successfully completed his/her Mini-Project in

"Weaponry Detection using Artificial Intelligence for Security Applications"

to our satisfaction and submitted the same during the academic year 2021 - 2022 towards the partial fulfilment of degree of **Master of Science in Data Science and Big Data Analytics** of Dr Vishwanath Karad MIT World Peace University under the School of Computer Science and Engineering, Department of Computer Science and Application, MIT WPU, Pune.

Prof. Dr. Shubhalaxmi Joshi	**Prof. Surabhi Thatte**	**Prof. Surabhi Thatte**
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MITWPU	**MIT WPU**	**MIT WPU**

ACKNOWLEDGEMENT

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Introduction

Domain

Artificial Intelligence and Deep Learning.

Motivation

Security is always a main concern in every domain, due to a rise in crime rate in a crowded event or suspicious lonely areas. Abnormal detection and monitoring have major applications of computer vision to tackle various problems. Due to growing demand in the protection of safety, security and personal properties, needs and deployment of video surveillance systems can recognize and interpret the scene and anomaly events play a vital role in intelligence monitoring. This paper implements automatic gun (or) weapon detection using a convolution neural network (CNN), Support Vector Machines (SVM) and Random Forest that come under classification.

Problem Statement

Weaponry Detection using Artificial Intelligence for Security Applications.Use various ML & DL Algorithms to classify images and compare their accuracy to understand the future scope.

Literature Survey

Weapon or Anomaly detection is the identification of irregular, unexpected, unpredictable, unusual events or items, which is not considered as normally occurring vent or regular item in a pattern or items present in a dataset and thus different from existing patterns. An anomaly is a pattern that occurs differently from a set of standard patterns. Therefore, anomalies depend on the phenomenon of interest. Object detection uses feature extraction and learning algorithms or models to recognize instances of various. categories of objects. The proposed implementation focuses on accurate gun detection and classification. Also concerned. with accuracy, since a false alarm could result in adverse responses. Choosing the right approach required making a proper trade-off between accuracy and speed.

Author	Dataset	Size of data	Pre-processing	Model Used	Output
RV College of Engineering ● Anuv Jain	COCO and self-created image dataset	3000+ images	Image labelling	Faster RCNN SSD	Faster RCNN gives more accuracy of 84.6% and SSD gives 73.8%
● Sanam Narejo ● Bishwajeet Pandey ● Doris Esenarro vargas ● Ciro Rodriguez ● M. Rizwan Anjum	Custom dataset	1000+ images	Image augmentation 416x416 pixels	YOLO	YOLO is faster for weapon detection

Solution Design

Solution Approach

Dataset is created, trained and fed to object classification algorithm. Based on application suitable classification algorithm (CNN, SVM, Random Forest algorithm) chosen for weapon detection. The approach addresses a problem of classification using various machine learning models like CNN, SVM, Random Forest algorithm.

Technology Stack

- Python
  Libraries:
  a) Python Imaging Library (pre-processing)
  b) Numpy for arrays
  c) sklearn.model_selection
  d) sklearn.ensemble
  e) pandas
  f) sklearn.metrics

- GPU for CNN AMD Ryzen processor and AMD Radeon Graphics

Design Model

Process Flow

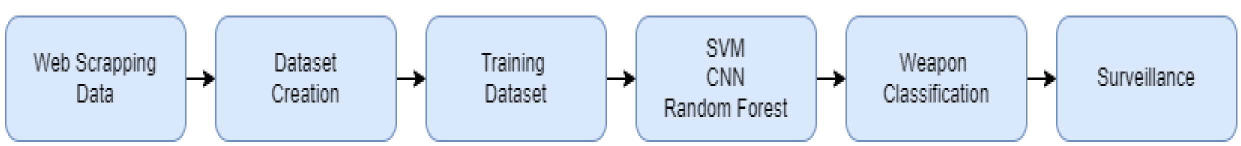


Fig (1) Process Flow Diagram

Dataset is created, trained and fed to object classification algorithm. Based on application suitable classification algorithm (CNN, SVM, Random Forest algorithm) chosen for weapon detection. The approach addresses a problem of classification using various machine learning models like CNN, SVM, Random Forest algorithm.

Solution Implementation and Results

<u>Obtaining Data</u>

We will be focusing on gathering images of weaponry from "Google Images". Around 1300+ images were collected. Out of which some were used as training data and rest were used for validation and testing. The weaponry was divided in to two different types viz,

- Gun (AK 47, AS 50 Sniper Rifle, DSR 50, M1911 Browning Rifle, Tracking Point Rifle, UZI)
- Knife

Sample Data

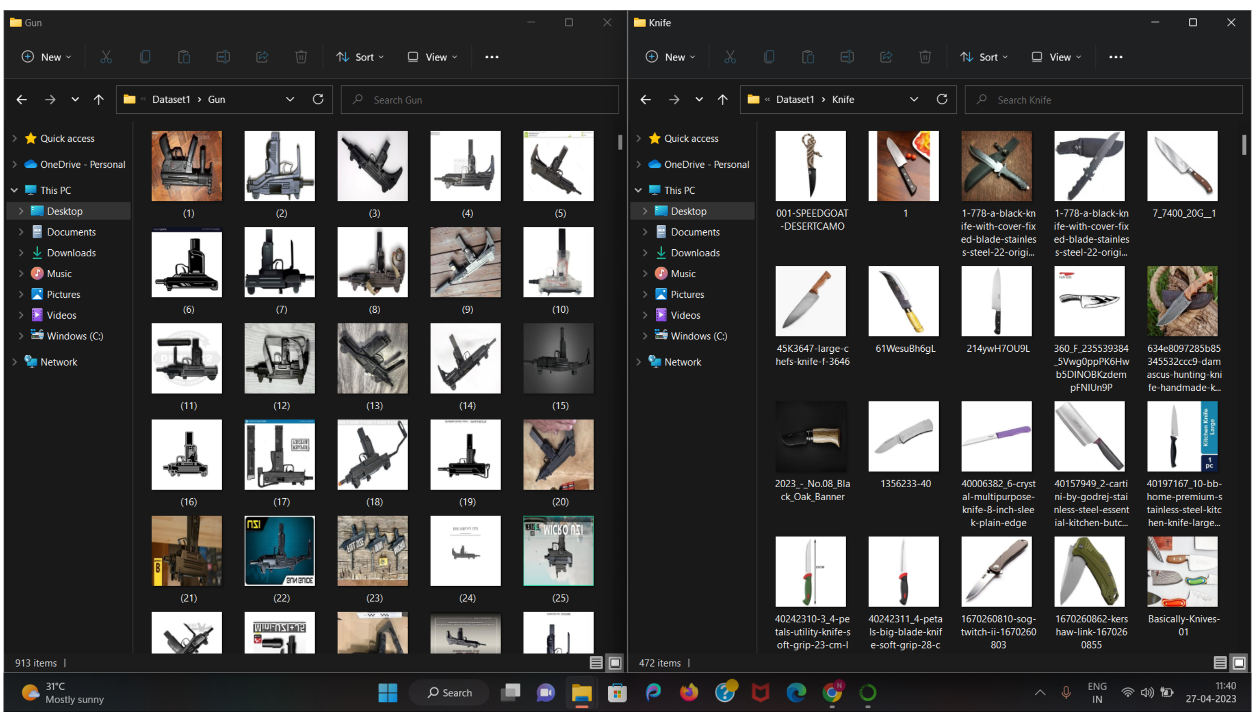


Fig (2) Images in dataset

The images were downloaded in bulk using **“Fatkun”** download tool.

EDA

a) Data Size and Distribution:

The dataset contains 1300+ images of weapons distributed among 2 classes. Each class has a different number of images, and it's important to understand the distribution of the data across these classes. Here is the distribution of images per class:

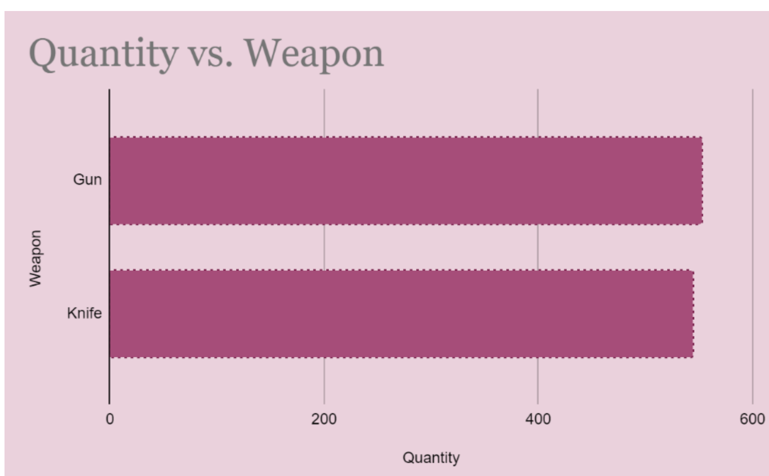
Gun: 553

Knife: 544

The number of images for each class have been kept nearly equal deliberately to avoid class imbalance.

Class Imbalance

A classification dataset with skewed class proportions is called as imbalanced class. Classes that make up a large proportion of the data set are called majority classes. Those that of smaller proportion are called minority classes.



The Fig (3) shows that class imbalance does not exist

b) Image Size and Type:

It's important to check the size and type of the images in the dataset. This will help us to understand the pre-processing required before feeding the images to the model. Here are some statistics regarding the image size and type:

Image Size: The images in the dataset have different sizes. The size of the largest image is 1280x960, and the smallest image is 259x194. This shows that the images are not standardized, and resizing might be required.

Image Type: The images are in the JPEG format.

Reason: Default Size of images for the input layer in CNN Algorithm is 256x256x3. Hence as we are working with image dataset containing multiple images of various sizes we convert all our images into size of 256x256x3.

c) Image Augmentation:

Image augmentation is an important step to improve the performance of the model during training. Augmentation can be done in several ways, including rotation, flipping, zooming, and adding noise. Here are some insights related to image augmentation:

Image Rotation: The images in the dataset can be rotated to create more variations. However, it's important to note that some weapons have a specific orientation, and rotation might not be applicable in all cases.

Image Flipping: Flipping can also be used to create more variations, but again, some weapons have a specific orientation, and flipping might not be applicable in all cases.

The website, https://pinetools.com/ was used for image augmentation. All the images were loaded in bulk and were flipped and rotated.

d) Class Distribution Visualization:

Visualizing the distribution of images per class can provide valuable insights into the dataset:

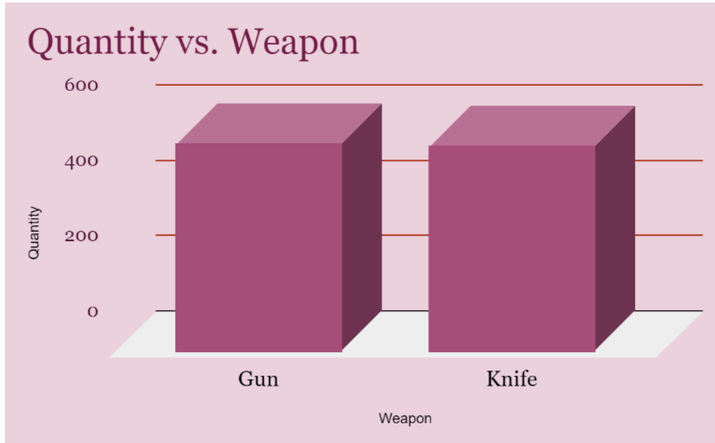


Fig (4) Image Distribution

Pre-Processing

a) Resolution

All the images thus collected were fitted into 256x256 resolution using the following python code

Pre-processing

In [2]:

```
from PIL import Image
import os

# directory
jpeg_dir = r'D:\PYTHON\Weapons\Knife'

# creating a new directory
if not os.path.exists('jpg_images'):
    os.makedirs('Knife')

# loops through all Jpg or Jpeg images and
for filename in os.listdir(jpeg_dir):
    if filename.endswith('.jpeg') or filename.endswith('.jpg'):
        # open the image
        image = Image.open(os.path.join(jpeg_dir, filename))
        # convert the image to JPEG format and resize to 256x256 dimensions
        image = image.convert('RGB').resize((256, 256))
        # save the image in the jpg_images directory
        new_filename = os.path.splitext(filename)[0] + '.jpeg'
        image.save(os.path.join('Knife', new_filename))
```

Fig (5) Python Pre-processing Code

b) Data Augmentation

The images were later flipped horizontally and vertically using pinetools.com

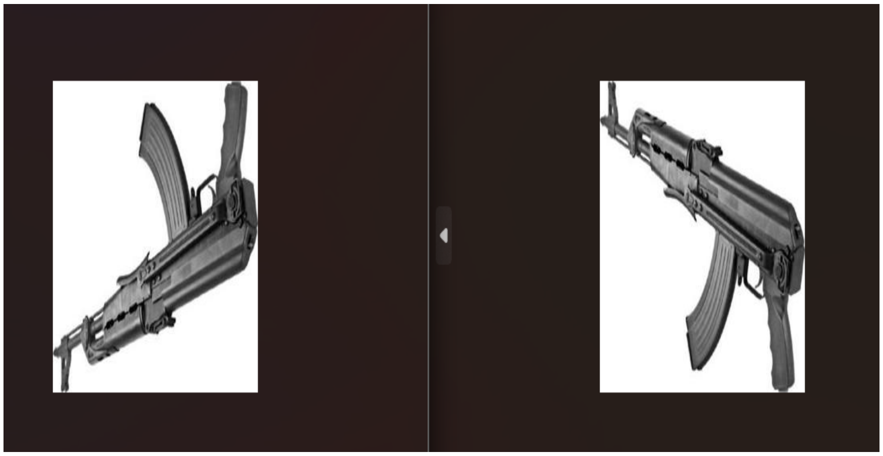


Fig (6) Data Augmentation in horizontal and vertical

Algorithms Used

The proposed models are supervised models of machine learning

1. CNN

A Convolutional Neural Network (CNN) is a type of deep learning algorithm that is particularly well-suited for image recognition and processing tasks. It is made up of multiple layers, including convolutional layers, pooling layers, and fully connected layers.

The convolutional layers are the key component of a CNN, where filters are applied to the input image to extract features such as edges, textures, and shapes. The output of the convolutional layers is then passed through pooling layers, which are used to down-sample the feature maps, reducing the spatial dimensions while retaining the most important information. The output of the pooling layers is then passed through one or more fully connected layers, which are used to make a prediction or classify the image.

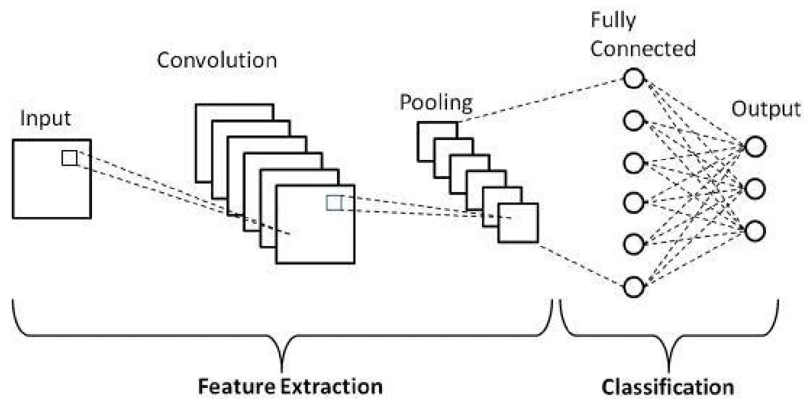


Fig (7) CNN Architecture

Limitations:

- Limited Input Size: CNNs are typically designed to work with fixed-size inputs. This means that if the input size of an image is too small or too large, the performance of the network may degrade.
- Lack of Rotation Invariance: CNNs are not inherently rotation invariant. This means that if an object in an image is rotated, the network may not recognize it correctly.
- Limited Interpretability: CNNs are often referred to as black box models because it can be challenging to understand how they make predictions. The intermediate layers of a CNN transform the input data into higher-level representations that are difficult to interpret.
- Overfitting: CNNs can easily overfit to the training data, especially when the number of training samples is small. This can lead to poor generalization performance on unseen data.

2. SVM

Support Vector Machine or SVM is one of the most popular Supervised Learning algorithms, which is used for Classification as well as Regression problems. However, primarily, it is used for Classification problems in Machine Learning.

The goal of the SVM algorithm is to create the best line or decision boundary that can segregate n-dimensional space into classes so that we can easily put the new data point in the correct category in the future. This best decision boundary is called a hyperplane.

SVM chooses the extreme points/vectors that help in creating the hyperplane. These extreme cases are called as support vectors, and hence algorithm is termed as Support Vector Machine. Consider the below diagram in which there are two different categories that are classified using a decision boundary or hyperplane

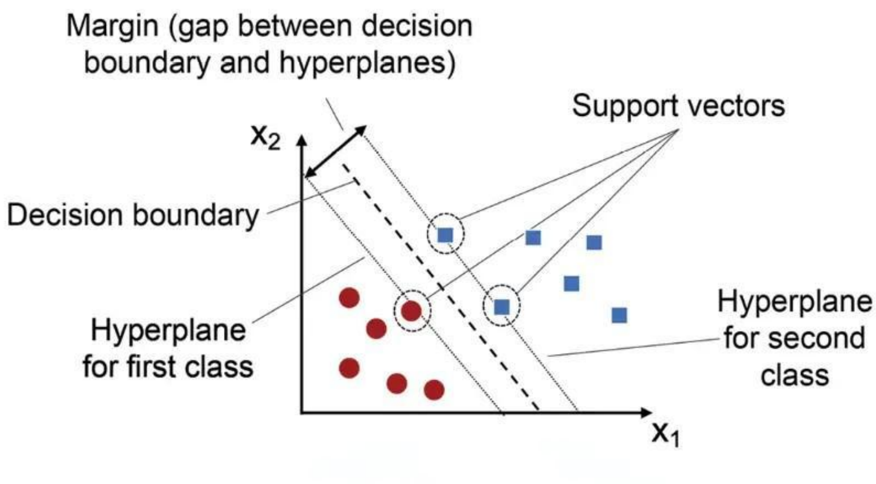


Fig (8) SVM Architecture

Limitations:

- Limited Feature Learning: SVM algorithm uses handcrafted features extracted from the image, which may not be optimal for the task at hand. In contrast, deep learning algorithms like CNN can automatically learn features from the data, leading to better performance.

- Limited Capacity: SVM algorithm may not have enough capacity to learn complex patterns and relationships in the image dataset, which can limit its performance.

- Sensitivity to Parameter Tuning: SVM algorithm is sensitive to the choice of kernel function and regularization parameter, which need to be carefully tuned for optimal performance. This can be time-consuming and require expert knowledge.

- Computationally Expensive: The SVM algorithm can be computationally expensive when dealing with large image datasets, as it requires solving a quadratic optimization problem.

- Limited Generalization: SVM algorithm may suffer from overfitting, especially when the number of training samples is small. This can limit its ability to generalize to unseen data.

3. Random Forest

Random Forest is a popular machine learning algorithm that belongs to the supervised learning technique. It can be used for both Classification and Regression problems in ML. It is based on the concept of ensemble learning, which is a process of combining multiple classifiers to solve a complex problem and to improve the performance of the model.

As the name suggests, **"Random Forest is a classifier that contains a number of decision trees on various subsets of the given dataset and takes the average to improve the predictive accuracy of that dataset."** Instead of relying on one decision tree, the random forest takes the prediction from each tree and based on the majority votes of predictions, and it predicts the final output.

The greater number of trees in the forest leads to higher accuracy and prevents the problem of overfitting.

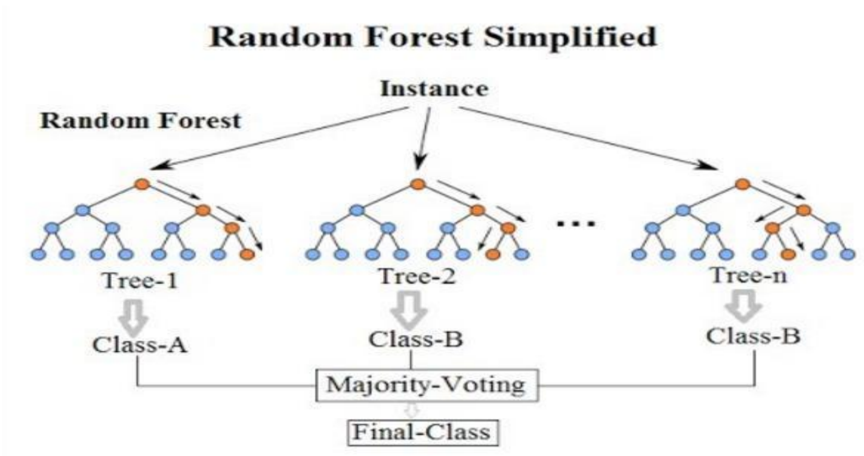


Fig (8) Random Forest Architecture

Limitations:

- Limited Feature Learning: RF algorithm uses handcrafted features extracted from the image, which may not be optimal for the task at hand. In contrast, deep learning algorithms like CNN can automatically learn features from the data, leading to better performance.

- Limited Capacity: RF algorithm may not have enough capacity to learn complex patterns and relationships in the image dataset, which can limit its performance.

- Lack of Interpretability: RF algorithm is not inherently interpretable. Although feature importance can be calculated, it is difficult to interpret the decision-making process of the algorithm, especially when dealing with high-dimensional image data.

- Computationally Expensive: The RF algorithm can be computationally expensive when dealing with large image datasets, as it requires training multiple decision trees.

- Limited Generalization: RF algorithm may suffer from overfitting, especially when the number of training samples is small. This can limit its ability to generalize to unseen data.

Results

Based on Accuracy

Companies use machine learning models to make practical business decisions, and more accurate model outcomes result in better decisions. The cost of errors can be huge, but optimizing model accuracy mitigates that cost. There is, of course, a point of diminishing returns when the value of developing a more accurate model won't result in a corresponding profit increase, but often it is beneficial across the board. A false positive cancer diagnosis, for example, costs both the hospital and the patient. The benefits of improving model accuracy help avoid considerable time, money, and undue stress.

Algorithm	Accuracy
CNN	96%
SVM	77%
Random Forest	88.6%

Every algorithm was run approximately 5-6 times with similar conditions and the accuracy for all the three algorithms proved to stay the same.

Formulae

1) CNN

The accuracy formula for CNN (Convolutional Neural Network) algorithm is the same as the formula for any other classification algorithm. It is defined as the ratio of the number of correctly classified samples to the total number of samples. Mathematically, it can be expressed as:

Accuracy = (Number of correctly classified samples) / (Total number of samples)

2) SVM

The accuracy formula for Support Vector Machine (SVM) algorithm used for image datasets is the same as the formula for any other classification algorithm. It is defined as the ratio of the number of correctly classified samples to the total number of samples. Mathematically, it can be expressed as:

Accuracy = (Number of correctly classified samples) / (Total number of samples)

3) Random Forest

The accuracy formula for Random Forest (RF) algorithm used for image datasets is the same as the formula for any other classification algorithm. It is defined as the ratio of the number of correctly classified samples to the total number of samples. Mathematically, it can be expressed as:

Accuracy = (Number of correctly classified samples) / (Total number of samples)

Conclusion and Future Work

Conclusion:

Hence, we can conclude that CNN has the highest accuracy which is 96%, followed by Random Forest which is 90.45% and SVM has the lowest accuracy of 77%.

Future Work

The problem statement can further be modified for inventory classification with respect to a business. A certain weaponry selling business may require inventory in the warehouse to be classified. Further-more we can use different prediction models to predict the amount and type of inventory required.

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