SASTRA

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END SEMESTER EXAMINATIONS NOV-2024
FINAL PROJECT REPORT

Submitted To:

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Title: DETECTION OF BONE FRACTURES USING MACHINE LEARNING TECHNIQUES.

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Course Code: CSE-425

Course Name: Machine Learning Essentials.

Semester : 7th Semester

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ABSTRACT

This study presents a machine learning-based approach for detecting bone fractures using X-ray images. With the increasing incidence of bone fractures globally, the research aims to assist medical professionals in providing fast and accurate diagnoses. Various machine learning algorithms, including Naïve Bayes, Decision Tree, Nearest Neighbors, Random Forest, and Support Vector Machine (SVM), were tested on a dataset containing X-ray images of fractured and non-fractured lower leg bones. The study highlights that SVM achieved the highest accuracy, making it a valuable tool for automated fracture detection.

INTRODUCTION

Project Objectives: The primary objective of this research is to develop an automated system capable of detecting bone fractures from X-ray images with high precision. By employing machine learning algorithms, the system aims to assist doctors in diagnosing fractures, which often requires manual inspection of numerous X-rays, a process prone to errors due to visual fatigue.

Problem Formulation

Bone fractures are a common injury, especially in the lower leg bones (tibia). Traditional methods of diagnosing fractures involve manual analysis by radiologists, which can be inefficient and prone to errors. The use of machine learning algorithms presents an opportunity to automate this process, providing more accurate results in less time. The research explores different algorithms to identify which can best detect and classify fractures using features extracted from X-ray images.

METHDOLOGY

DATASET

After Preprocessing the Dataset I found that my entire dataset is divided mainly into 3 folders named as TRAIN , TEST AND VALIDATION.
Where the TRAIN folder nearly consists of 4000 X-Ray images.
The TEST folder consists of nearly 500 images and the VAL folder consists of nearly 429 images.

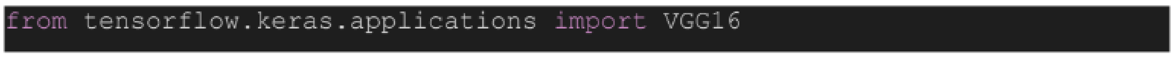
Link to the Dataset :
https://www.kaggle.com/datasets/ahmedashrafahmed/bone-fracture.

Data Augmentation to improve the model's performance and predictability

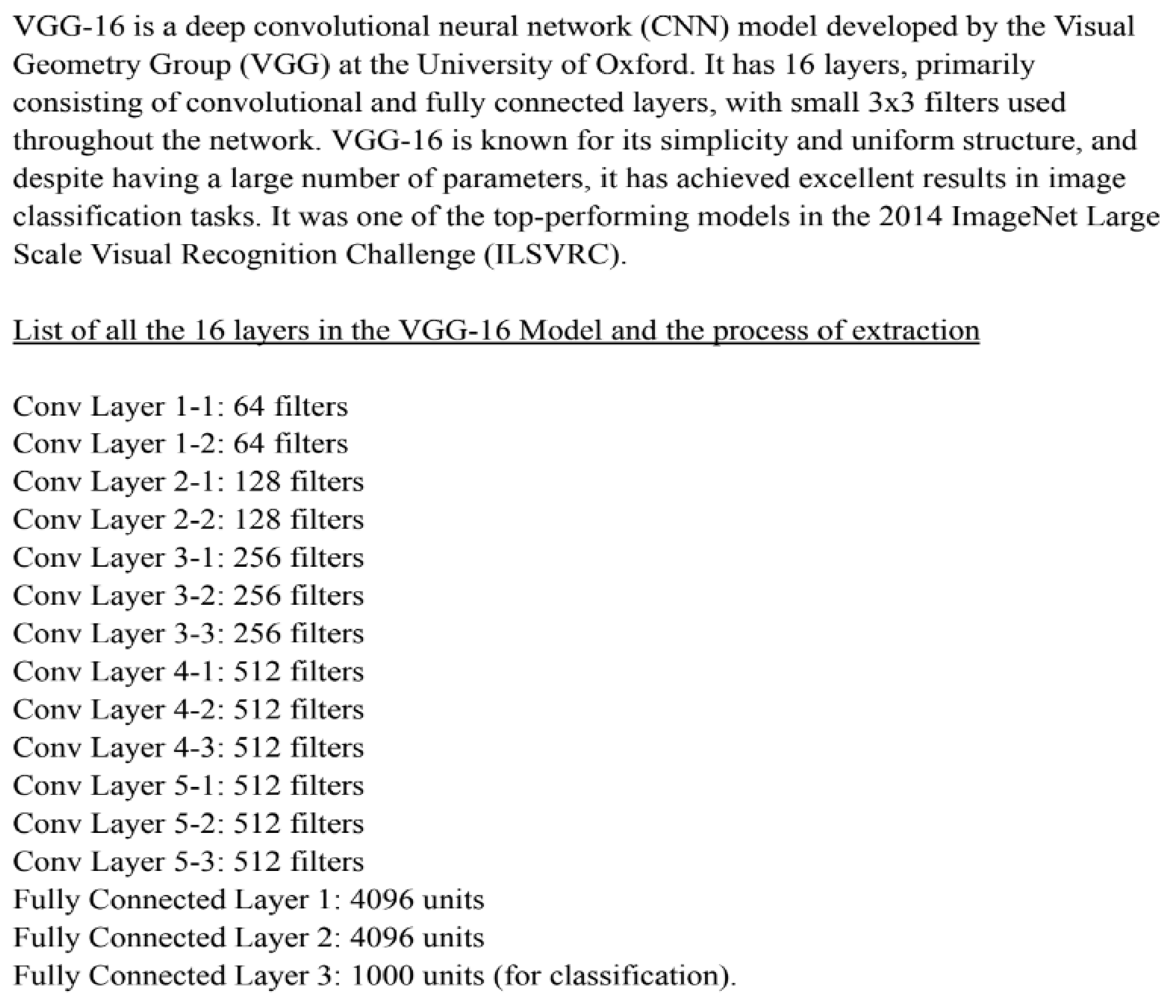
Data augmentation is a technique used in machine learning to increase a dataset's diversity without collecting new data. It involves creating modified versions of existing data, such as images or text, through transformations like flipping, rotating, cropping, or adding noise. This helps improve model performance by making it more robust and reducing overfitting. Data augmentation is particularly useful in computer vision tasks but is also applied in other domains like natural language processing.

Feature Extraction using VGG-16

Importing the inbuilt VGG-16 models for the purpose of feature extraction



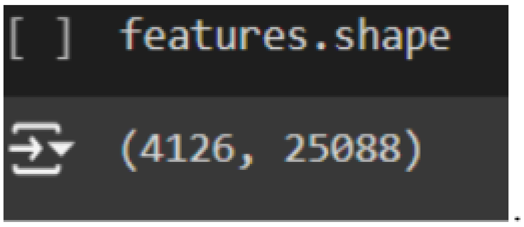
```python
from tensorflow.keras.applications import VGG16
```



VGG-16 is a deep convolutional neural network (CNN) model developed by the Visual Geometry Group (VGG) at the University of Oxford. It has 16 layers, primarily consisting of convolutional and fully connected layers, with small 3x3 filters used throughout the network. VGG-16 is known for its simplicity and uniform structure, and despite having a large number of parameters, it has achieved excellent results in image classification tasks. It was one of the top-performing models in the 2014 ImageNet Large Scale Visual Recognition Challenge (ILSVRC).

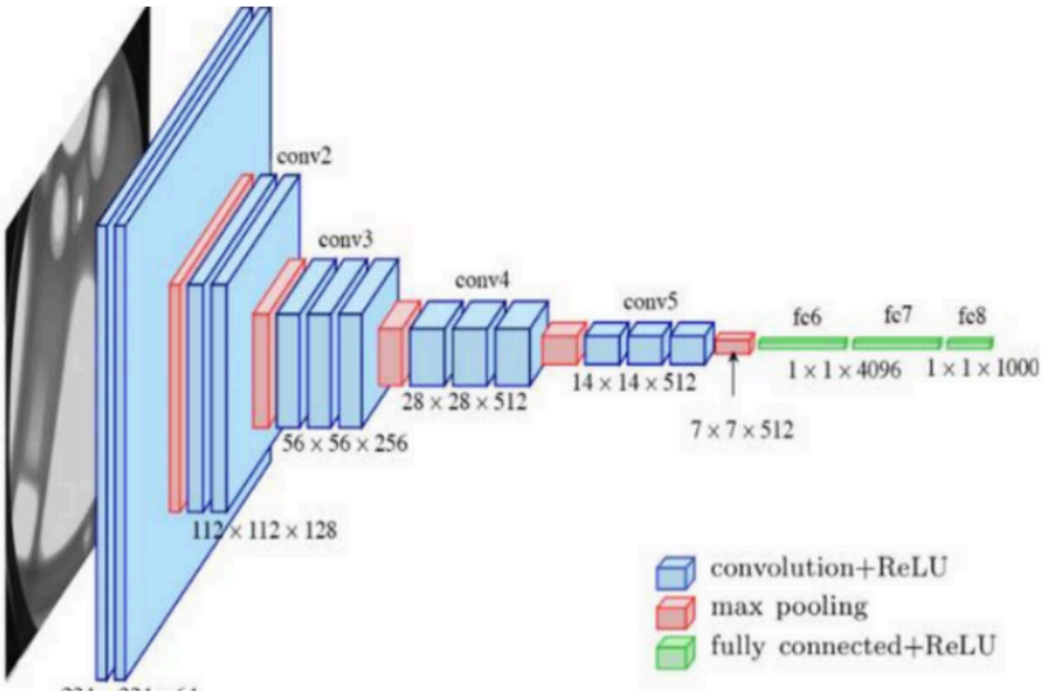
List of all the 16 layers in the VGG-16 Model and the process of extraction

Conv Layer 1-1: 64 filters
Conv Layer 1-2: 64 filters
Conv Layer 2-1: 128 filters
Conv Layer 2-2: 128 filters
Conv Layer 3-1: 256 filters
Conv Layer 3-2: 256 filters
Conv Layer 3-3: 256 filters
Conv Layer 4-1: 512 filters
Conv Layer 4-2: 512 filters
Conv Layer 4-3: 512 filters
Conv Layer 5-1: 512 filters
Conv Layer 5-2: 512 filters
Conv Layer 5-3: 512 filters
Fully Connected Layer 1: 4096 units
Fully Connected Layer 2: 4096 units
Fully Connected Layer 3: 1000 units (for classification).

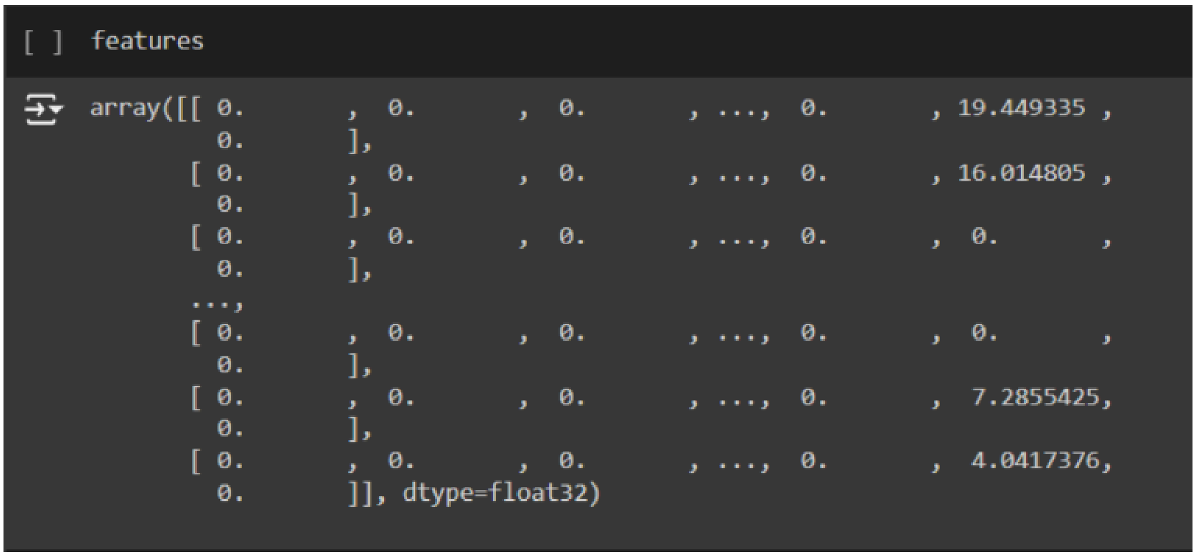


```
[ ]  features.shape

     (4126, 25088)
```

ARCHITETURAL DIAGRAM OF VGG-16



Then the features obtained have been converted into an array to pass into the models that have been implemented.



```
[ ]  features

array([[ 0.        ,  0.        ,  0.        , ...,  0.        , 19.449335 ,
         0.        ],
       [ 0.        ,  0.        ,  0.        , ...,  0.        , 16.014805 ,
         0.        ],
       [ 0.        ,  0.        ,  0.        , ...,  0.        ,  0.        ,
         0.        ],
       ...,
       [ 0.        ,  0.        ,  0.        , ...,  0.        ,  0.        ,
         0.        ],
       [ 0.        ,  0.        ,  0.        , ...,  0.        ,  7.2855425,
         0.        ],
       [ 0.        ,  0.        ,  0.        , ...,  0.        ,  4.0417376,
         0.        ]], dtype=float32)
```

Splitting the dataset to test and train on a ratio of 80:20 so that more number of images included for training would improve the model performance and its ability to predict new images given as input.

```
# Split into test and training sets
X_train, X_test, y_train, y_test = train_test_split(features, labels,
test_size=0.2, random_state=42)
```

IMPLEMENTATION OF MODELS / RESULTS OBTAINED

1. Support Vector Machine (SVM)

Support Vector Machine (SVM) is a supervised machine learning algorithm commonly used for classification and regression tasks. It works by finding the hyperplane that best separates data into different classes in a multi-dimensional space. SVM is effective in high-dimensional spaces and is particularly useful when the classes are well-separated. It can use kernel tricks to handle non-linear boundaries by mapping input features into higher dimensions. SVM is known for its robustness in avoiding overfitting, especially with smaller datasets.

ACCURACY OBTAINED : 100%

2. Decision Tree classifier

A Decision Tree classifier is a supervised machine learning algorithm used for classification tasks. It works by splitting data into subsets based on feature values, forming a tree-like structure of decisions. Each internal node represents a feature, branches represent decisions, and leaf nodes correspond to the class label. The tree recursively splits the dataset to maximize the information gain (or minimize impurity) at each step. Decision Trees are easy to interpret but can overfit the data if not pruned

Properly.

Accuracy Obtained : 93.704 %.

3. Random Forest classifier

A Random Forest classifier is an ensemble learning method that builds multiple decision
trees during training and outputs the mode of the classes (classification) of the individualtrees. It reduces overfitting by averaging the results of these multiple trees, making it more robust and accurate than a single decision tree. Random Forests are effective for both classification and regression tasks, handling large datasets with higher dimensionality, and offering feature importance metrics that help identify the most relevant features in a dataset.

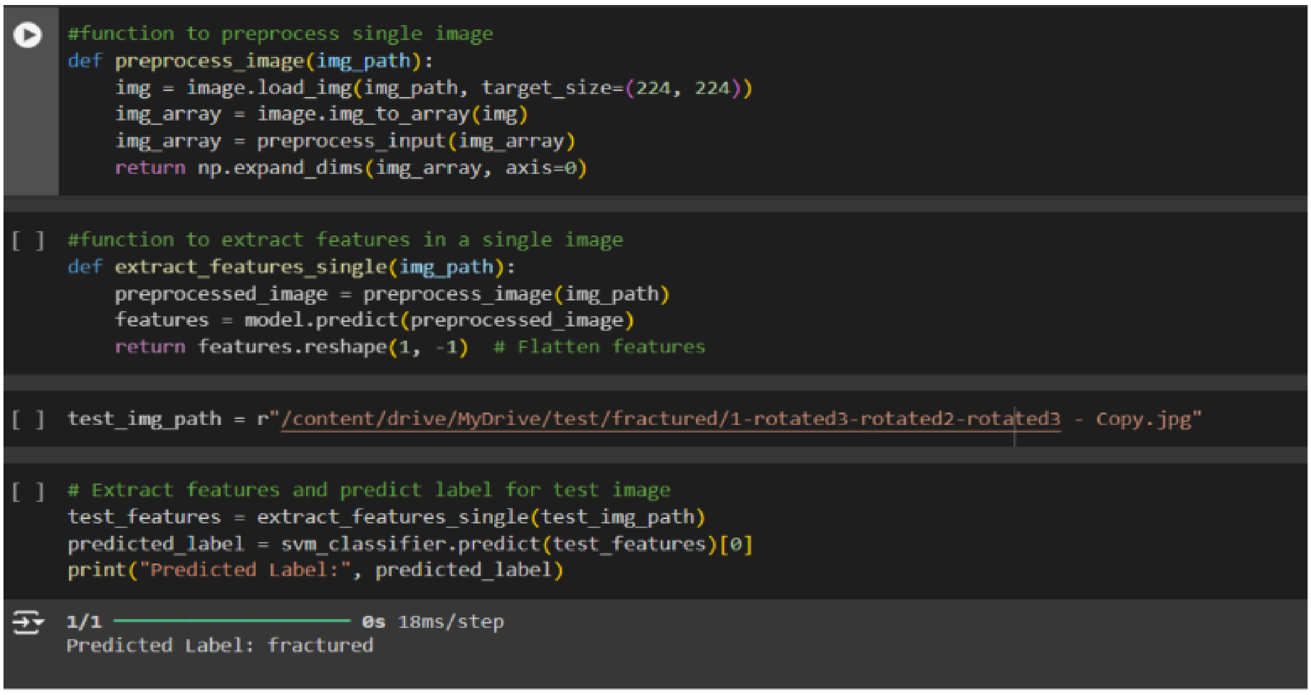
Accuracy obtained : 99.75%.

4. KNN Classifier

The K-Nearest Neighbors (KNN) classifier is a simple, non-parametric algorithm used for classification and regression tasks. It works by finding the 'k' nearest data points (neighbors) to a given input and assigning the most common class label among them. KNN relies on distance metrics like Euclidean distance to measure similarity. It’s computationally expensive, especially with large datasets, since classification requires comparing the input to every data point. KNN is sensitive to the choice of 'k' and requires proper scaling of features for optimal performance.

Accuracy Obtained : 96.97%

The above mentioned models have been implemented and the accuracy for each model have been obtained and the models have been tested against new images basing on which they were able to correctly classify the newly imputed X-ray image and produce the result.



```
#function to preprocess single image
def preprocess_image(img_path):
    img = image.load_img(img_path, target_size=(224, 224))
    img_array = image.img_to_array(img)
    img_array = preprocess_input(img_array)
    return np.expand_dims(img_array, axis=0)
```

```
[ ] #function to extract features in a single image
    def extract_features_single(img_path):
        preprocessed_image = preprocess_image(img_path)
        features = model.predict(preprocessed_image)
        return features.reshape(1, -1)  # Flatten features
```

```
[ ] test_img_path = r"/content/drive/MyDrive/test/fractured/1-rotated3-rotated2-rotated3 - Copy.jpg"
```

```
[ ] # Extract features and predict label for test image
    test_features = extract_features_single(test_img_path)
    predicted_label = svm_classifier.predict(test_features)[0]
    print("Predicted Label:", predicted_label)
```

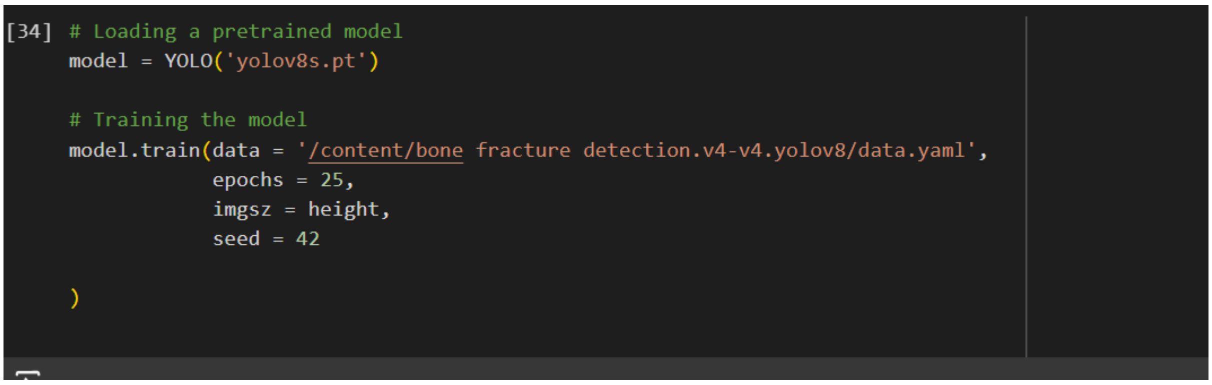
```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 18ms/step
Predicted Label: fractured
```

<u>**RESULTS EXPANDED USING YOLO V8**</u>

<u>ALL ABOUT YOLO V8</u>

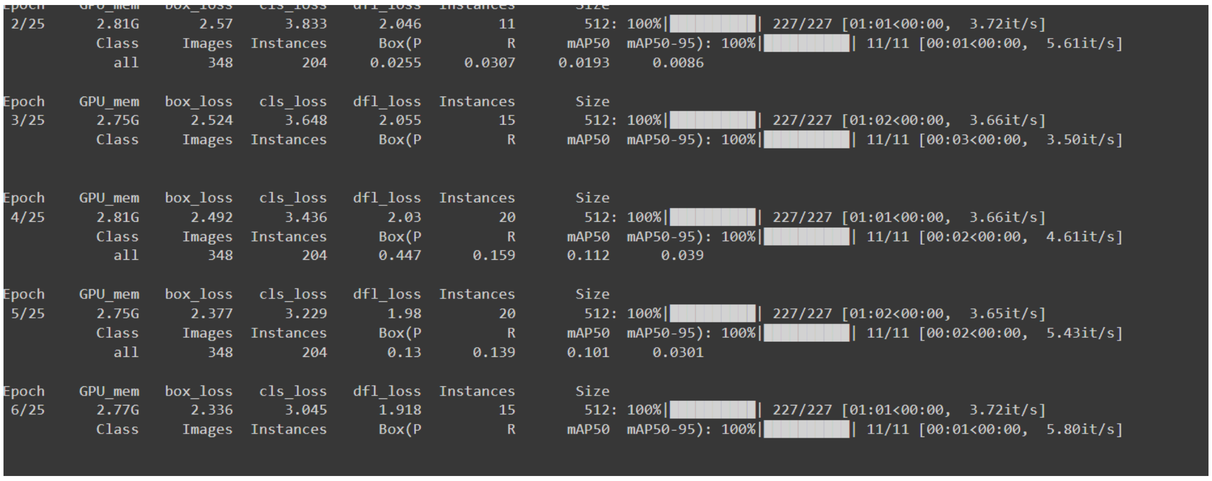
YOLOv8 (You Only Look Once, version 8) is the latest iteration of the YOLO series, designed for real-time object detection, classification, and segmentation. It builds upon the advancements made in YOLOv5, incorporating state-of-the-art features to enhance speed and accuracy. YOLOv8 uses a combination of anchor-free detection mechanisms and efficient neural network architectures, allowing it to perform well on smaller objects and crowded scenes. It supports tasks like object detection, instance segmentation, and keypoint detection with enhanced precision.

YOLOv8 is known for its lightweight model and scalability across various devices, from edge devices to powerful GPUs. It achieves this through optimized training techniques, model pruning, and quantization strategies. The model's performance has been fine-tuned using advanced techniques like mosaic augmentation, adaptive training, and enhanced non-max suppression (NMS) for better localization of objects.



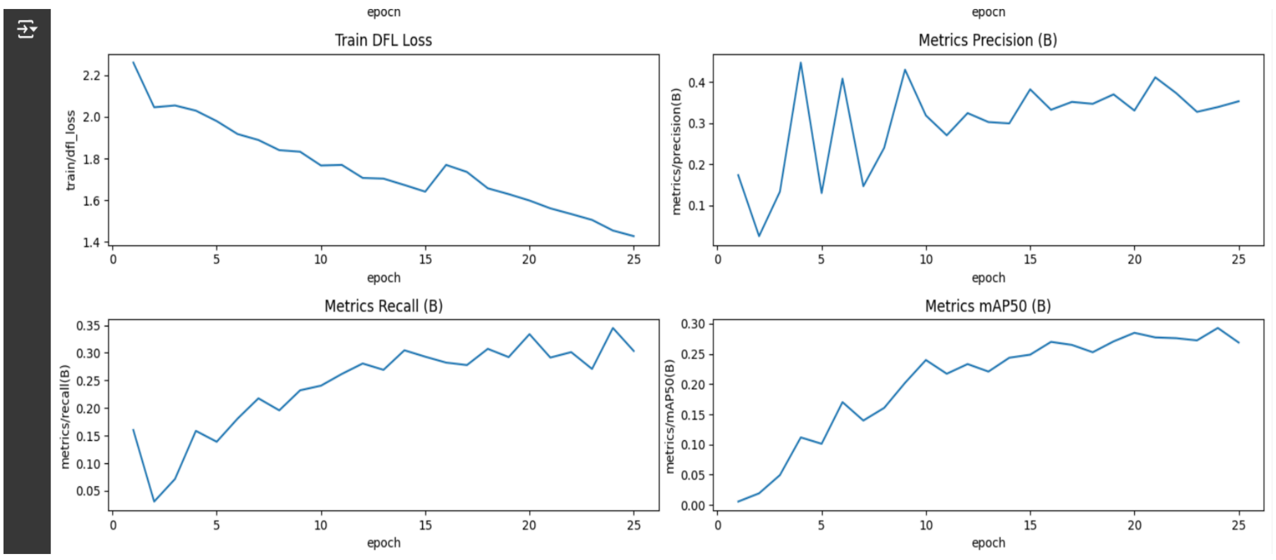
```
[34] # Loading a pretrained model
     model = YOLO('yolov8s.pt')

     # Training the model
     model.train(data = '/content/bone fracture detection.v4-v4.yolov8/data.yaml',
                 epochs = 25,
                 imgsz = height,
                 seed = 42

     )
```

Running the EPOCH :

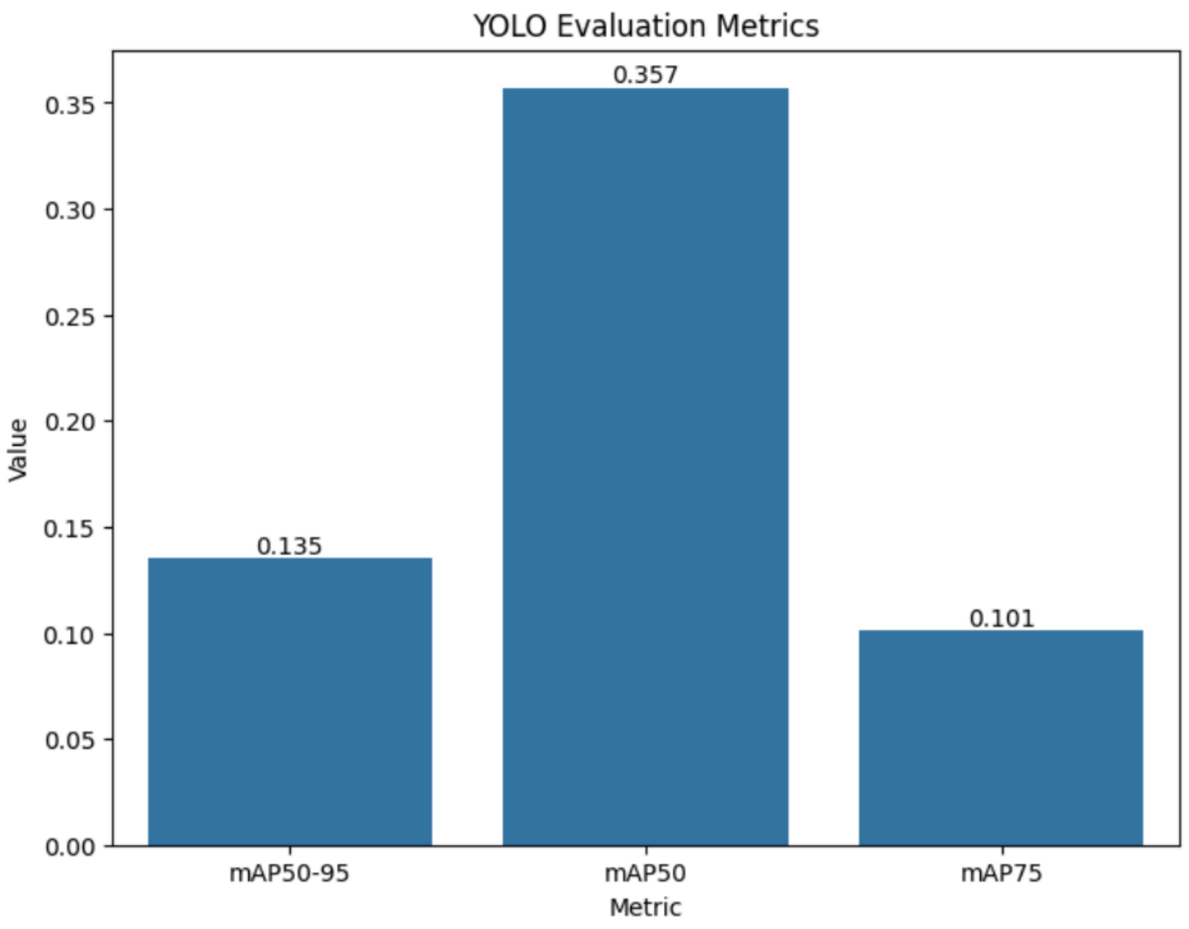


```
  2/25      2.81G       2.57      3.833      2.046         11        512: 100%|██████████| 227/227 [01:01<00:00,  3.72it/s]
            Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 100%|██████████| 11/11 [00:01<00:00,  5.61it/s]
              all        348        204     0.0255     0.0307     0.0193     0.0086

Epoch    GPU_mem   box_loss   cls_loss   dfl_loss  Instances       Size
  3/25      2.75G      2.524      3.648      2.055         15        512: 100%|██████████| 227/227 [01:02<00:00,  3.66it/s]
            Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 100%|██████████| 11/11 [00:03<00:00,  3.50it/s]


Epoch    GPU_mem   box_loss   cls_loss   dfl_loss  Instances       Size
  4/25      2.81G      2.492      3.436       2.03         20        512: 100%|██████████| 227/227 [01:01<00:00,  3.66it/s]
            Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 100%|██████████| 11/11 [00:02<00:00,  4.61it/s]
              all        348        204      0.447      0.159      0.112      0.039

Epoch    GPU_mem   box_loss   cls_loss   dfl_loss  Instances       Size
  5/25      2.75G      2.377      3.229       1.98         20        512: 100%|██████████| 227/227 [01:02<00:00,  3.65it/s]
            Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 100%|██████████| 11/11 [00:02<00:00,  5.43it/s]
              all        348        204       0.13      0.139      0.101     0.0301

Epoch    GPU_mem   box_loss   cls_loss   dfl_loss  Instances       Size
  6/25      2.77G      2.336      3.045      1.918         15        512: 100%|██████████| 227/227 [01:01<00:00,  3.72it/s]
            Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 100%|██████████| 11/11 [00:01<00:00,  5.80it/s]
```

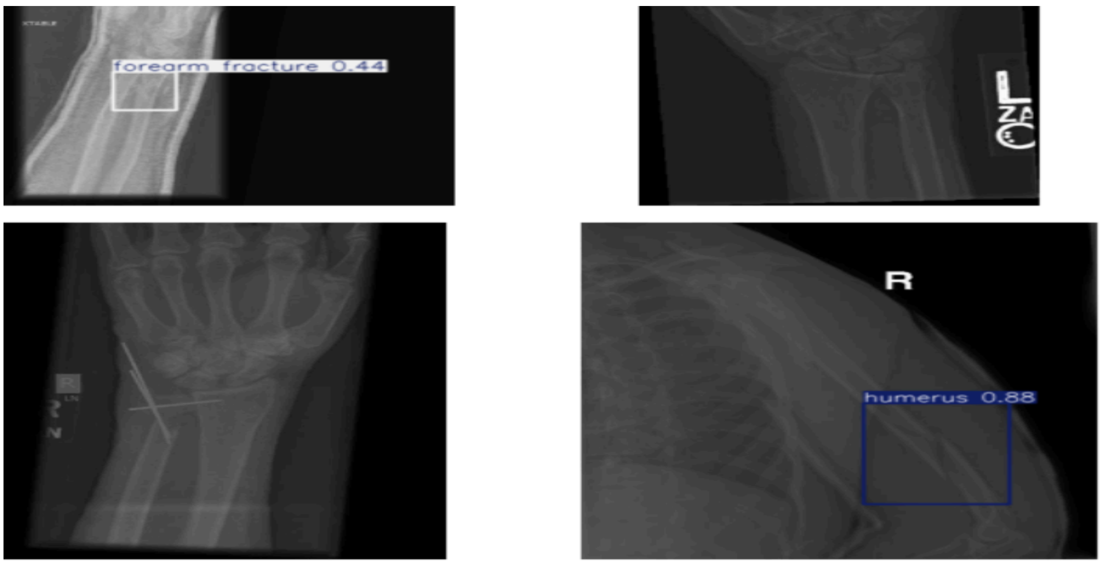
PLOTTING THE METRICS LOSS AND RECALL VALUES :



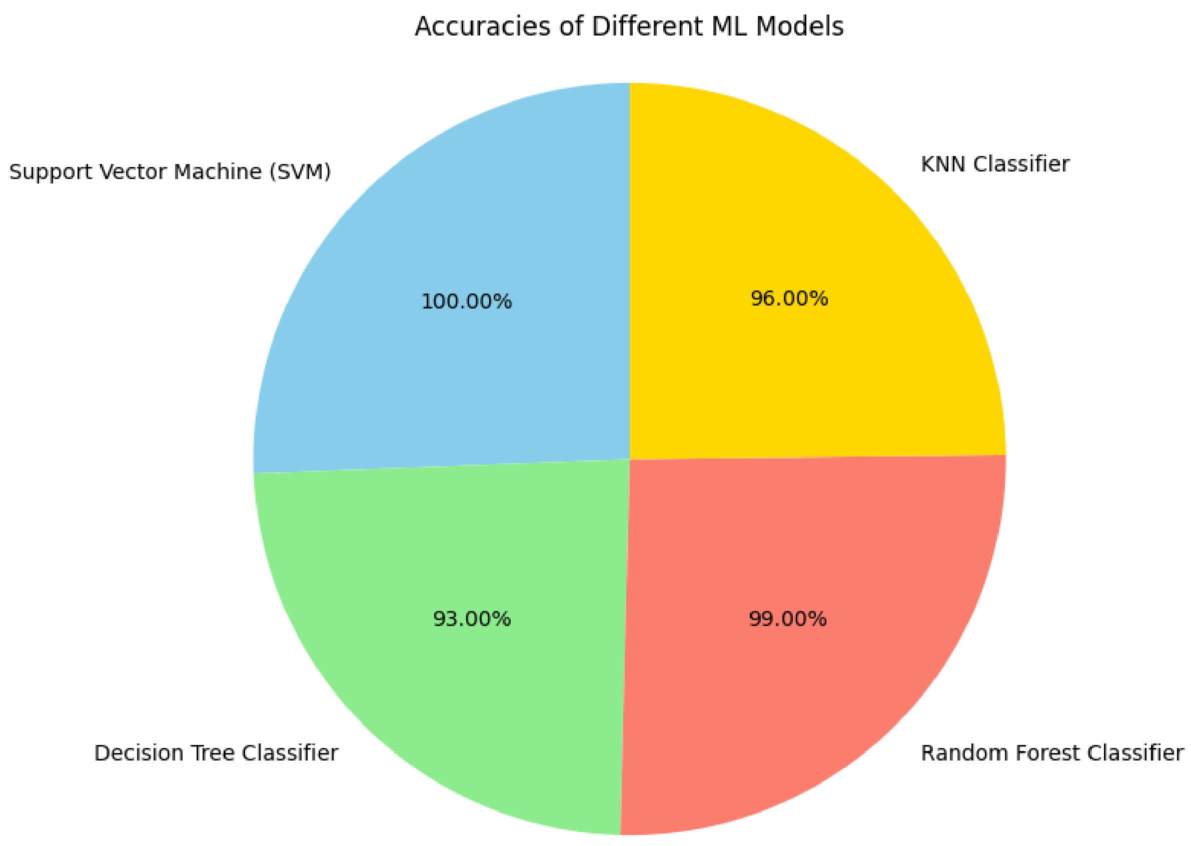
EVALUATION OF THE MODEL :



The model YOLOV8 is successfully able to detect bone Fractures



FINAL CONCLUSION



MODELS USED	**EVALUATION METRICS**	**RESULTS OBTAINED**
KNN Classifier	Accuracy	96%
Decision Tree Classifier	Accuracy	93%
Random forest	Accuracy	99.5%
SVM (Support Vector Machine)	Accuracy	100%
YOLO V8	mAP5095,mAP75,mAP50	0.135,0.357,0.101

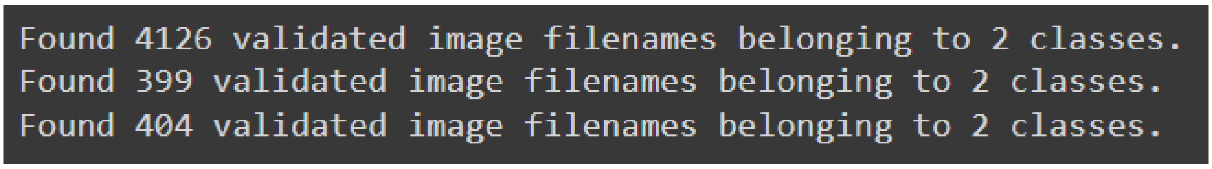
Link for collab: MLE END SEM.ipynb

RESULTS EXPANSION USING CNN

A Convolutional Neural Network (CNN) is a deep learning model designed for processing structured grid data, such as images. It uses convolutional layers to automatically extract features from input data by applying filters (or kernels). The layers are designed to capture spatial hierarchies in data, making CNNs effective for image and video analysis. Key components include convolutional layers, pooling layers, and fully connected layers. The convolutional layers detect patterns, pooling layers reduce dimensionality, and fully connected layers output predictions. CNNs are widely used for tasks like image classification, object detection, and facial recognition due to their ability to learn complex features efficiently.

DATA AUGMENTATION

Data augmentation is a technique used in machine learning to increase the diversity of training data without actually collecting new data. It involves applying transformations like rotation, flipping, scaling, and cropping to existing data. This helps improve model generalization by reducing overfitting and allowing the model to learn from a wider range of variations. Data augmentation is especially useful in tasks like image classification, where diverse input data can enhance model performance.



```
Found 4126 validated image filenames belonging to 2 classes.
Found 399 validated image filenames belonging to 2 classes.
Found 404 validated image filenames belonging to 2 classes.
```

MAKING UP OF CNN MODEL

Conv2D (conv2d): This convolutional layer has 32 filters, each with a size of (3x3), extracting features such as edges or textures from the input image. The output shape is (222, 222, 32), meaning 32 feature maps of size 222x222.

Batch Normalization (batch_normalization): This layer normalizes the outputs of the previous layer to speed up training and improve performance by reducing internal covariate shift.

MaxPooling2D (max_pooling2d): This layer downsamples the input by taking the maximum value over a (2x2) pooling window, reducing the spatial dimensions to (111, 111, 32), which helps in reducing computational complexity.

Conv2D (conv2d_1): This is another convolutional layer, with 64 filters and an output shape of (109, 109, 64), allowing the model to capture more complex patterns by looking at a wider range of features in the image.

Batch Normalization (batch_normalization_1): Similar to the previous normalization layer, this one ensures that the activations from the second convolutional layer are standardised.

MaxPooling2D (max_pooling2d_1): It reduces the spatial size to (54, 54, 64) with a pooling window, further simplifying the feature maps while retaining important information.

Dropout (dropout): This layer helps prevent overfitting by randomly setting a fraction of input units to zero during training. It encourages the network to generalize better.

Conv2D (conv2d_2): Another convolutional layer with 128 filters, producing feature maps of size (52, 52, 128), enabling the network to extract even higher-level features.

Batch Normalization (batch_normalization_2): Similar to the previous batch normalization layers, it standardizes the outputs from the third convolutional layer to enhance training speed and stability.

MaxPooling2D (max_pooling2d_2): This layer further reduces the dimensions to (26, 26, 128), keeping essential information while reducing the computational load.

Dropout (dropout_1): Another dropout layer to combat overfitting, applied after the third pooling layer.

Flatten (flatten): This layer flattens the multidimensional output from the previous layer into a one-dimensional vector (86,528 elements), preparing the data for the fully connected layer.

Dense (dense): This is a fully connected layer with 256 units, responsible for combining all features and making the final decision or prediction.

In total The CNN architecture consists of 13 Layers.

EPOCH WISE EVALUATION FOR THE MODEL

The model was trained for nearly 30 EPOCH and the performance improved significantly as the training progressed.

Key observations made after the EPOCH evaluation:

Accuracy Progression: The model's accuracy steadily increased from around 48.7% in the first epoch to over 90% by epoch 30. This indicates that the model was learning and improving throughout the training process.

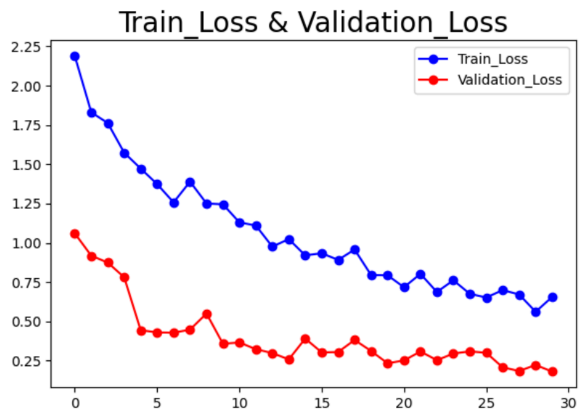
Loss Reduction: The training loss decreased from an initial value of around 2.5 in the first epoch to 0.76 by epoch 30, which is a sign of model convergence. Lower loss values typically indicate that the model is making better predictions.

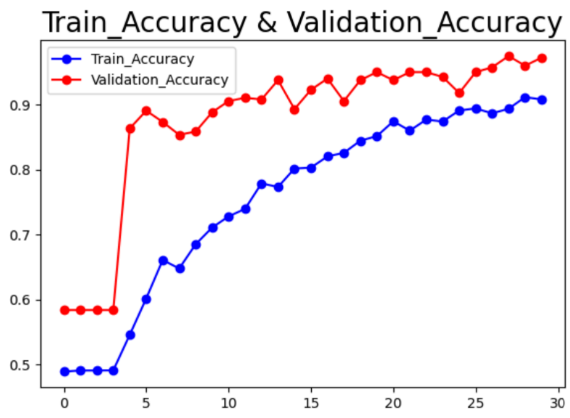
AUC Improvement: The AUC (Area Under the Curve) metric, which measures the model's ability to distinguish between classes, improved from 0.49 to 0.97, showing an increase in the model's ability to perform binary classification effectively.

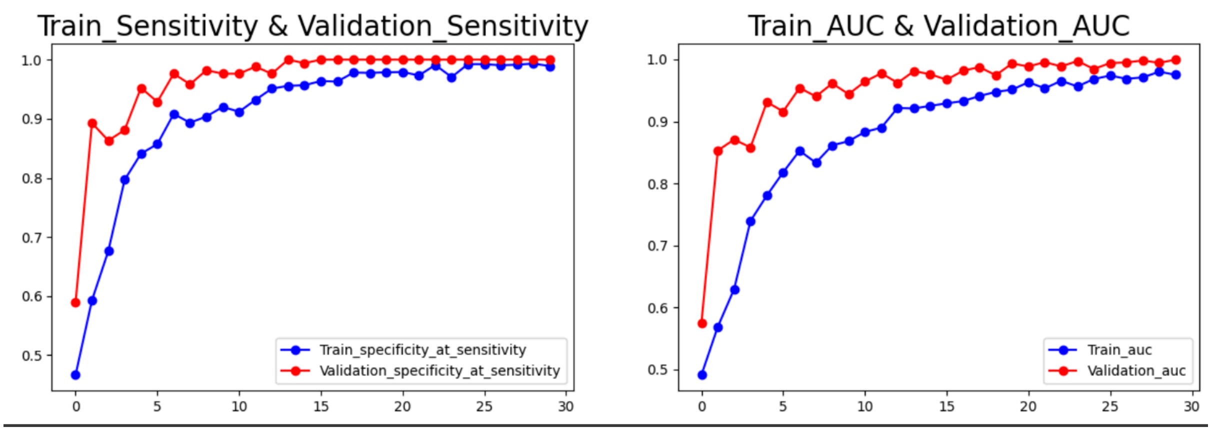
Validation Accuracy: The validation accuracy started around 63.7% and improved to over 97% by epoch 30. The high validation accuracy, in combination with the low validation loss (0.17), suggests that the model generalizes well to unseen data.

Specificity at Sensitivity: The specificity at a given sensitivity threshold increased, reaching values close to 1.0, indicating that the model is highly accurate in distinguishing between the classes while maintaining sensitivity.

Final Results: By the final epoch, The model achieved an impressive validation accuracy of 97.7%, with a validation AUC of 0.9996, meaning the model is performing almost perfectly in classifying the validation data.







From the above graphs we can infer that:

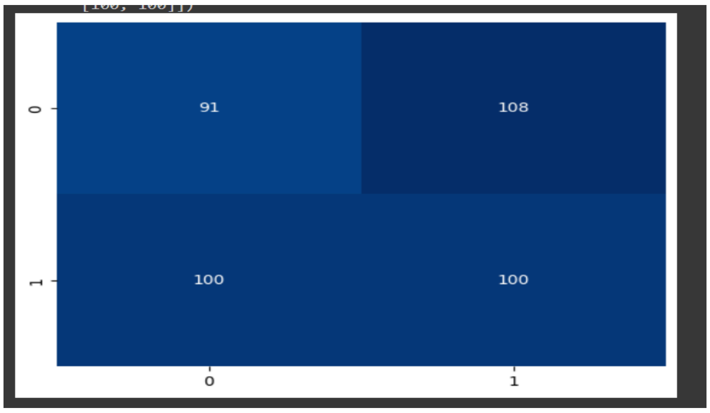
Sensitivity & Specificity: Both train and validation sensitivity improve as the epochs increase, with validation showing consistently higher values. This indicates that the model is becoming more adept at identifying true positives over time, with validation performance slightly better.

AUC: The AUC (Area Under the ROC Curve) improves steadily for both training and validation, but validation AUC surpasses training, showing that the model generalizes well.

Loss: Training and validation loss both decrease significantly, though the validation loss stabilizes at a lower value than the training loss. This suggests the model is learning effectively, with no major overfitting issues.

Accuracy: Both training and validation accuracy improve, with validation accuracy being consistently higher. This suggests that the model performs better on unseen data than on the training set.

<u>**CONFUSION MATRIX**</u>



From the confusion matrix we infer that :

True Negatives (TN): The model correctly predicted 91 negative instances (class 0).

False Positives (FP): It incorrectly predicted 108 instances as positive when they were actually negative.

False Negatives (FN): The model incorrectly predicted 100 instances as negative when they were actually positive.

True Positives (TP): It correctly predicted 100 positive instances (class 1).

FUTURE SCOPE

The potential for future advancements in bone fracture detection using machine learning is vast. Improvements in model accuracy and efficiency can be achieved by integrating more complex architectures like transformers or refining existing models with a broader dataset encompassing various fracture types and bones. Additionally, real-time analysis and mobile applications could extend this technology's reach, making it accessible for remote or underserved areas. Future research might also explore multimodal approaches, combining X-rays with CT or MRI data for comprehensive diagnostic capabilities.

FINAL CONCLUSION

This study demonstrates the effectiveness of machine learning techniques, particularly SVM and YOLOv8, in detecting bone fractures from X-ray images. With high accuracy and improved automation, these models offer a promising tool for medical professionals, enhancing diagnostic speed and accuracy. The results underscore the potential for AI-driven solutions to support healthcare professionals in making informed and timely diagnoses, particularly in resource-limited settings.

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SELF DECLARATION

I, Trilok Sai Vaddanam, a student of B.Tech in Computer Science & Business Systems, declare that the project titled "Detection of Bone Fractures Using Machine Learning Techniques" is my original work. I have conducted the research and implementation independently, with guidance from my instructor, Dr. Swetha Vardharajan. The information and content in this report, including the data sources and code implementation, are accurate and relevant to the best of my knowledge. Any assistance received and sources consulted have been duly acknowledged in the references section. This project was completed as part of the requirements for the Machine Learning Essentials course (Course Code: CSE-425) in the 7th semester.

THANK YOU