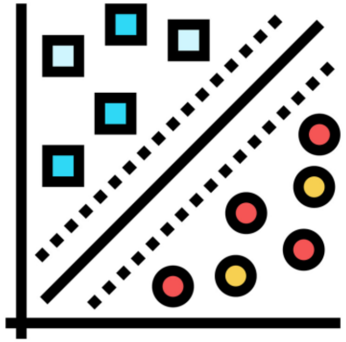
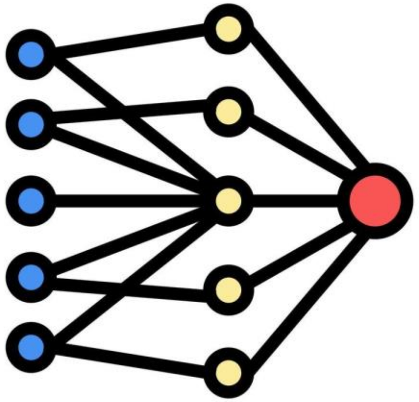
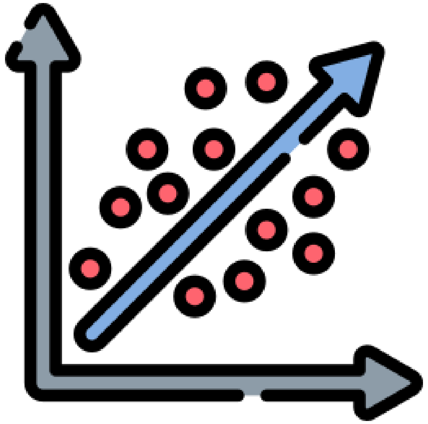
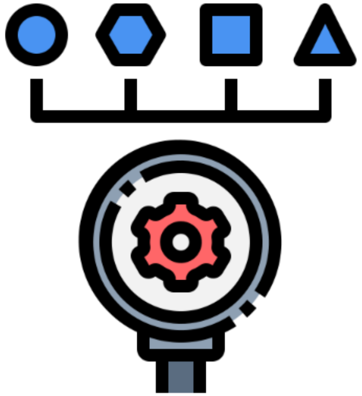
Comparative Analysis of SVM, CNN, and XGBoost

For Binary and Multi-Class Medical Image Classification on Chest X-ray and Brain Tumor Datasets









Datasets Used:

A. Chest X-Ray Dataset: [11]

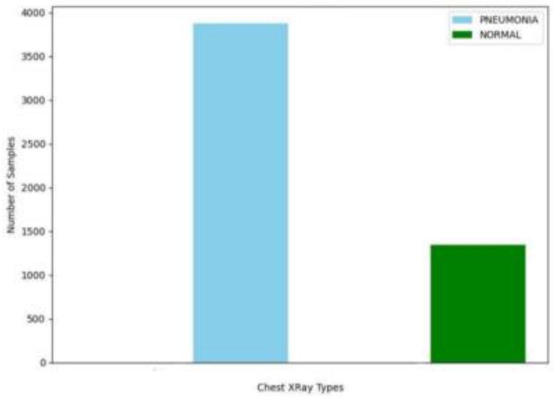


Figure 1. Histogram Visualization of Chest X-ray Dataset (5856 images)

a) Pneumonia (3875 images) b) Normal (1341 images)

Figure 2: Two distinct Classes of Chest X-ray Dataset (pixel dimension: 1024 X 680)

B. Brain Tumor Dataset: [12]

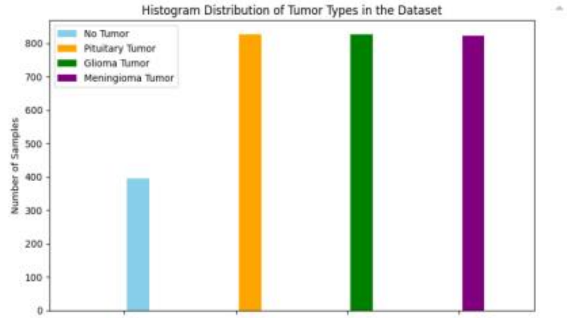
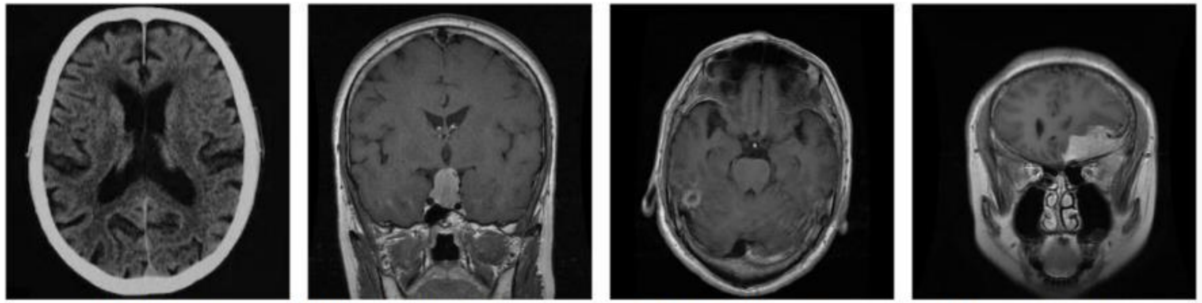


Figure 3: Histogram Visualization of Brain Tumor Dataset. (2870 images)



a) No tumour (395 images) b) Pituitary tumour (827 images) c) Glioma tumour (826 images) d) Meningioma tumour (822 images)

Figure 4: Four distinct Classes of Brain Tumor Dataset. (512 X 512)

Each image has a resolution of 2,000 pixels in width and height, stored as 8-bit grayscale JPEG files.

A. Standalone ML

I. SVM with PCA

Figure 5. Workflow Model for SVM

II. Raw XGBoost

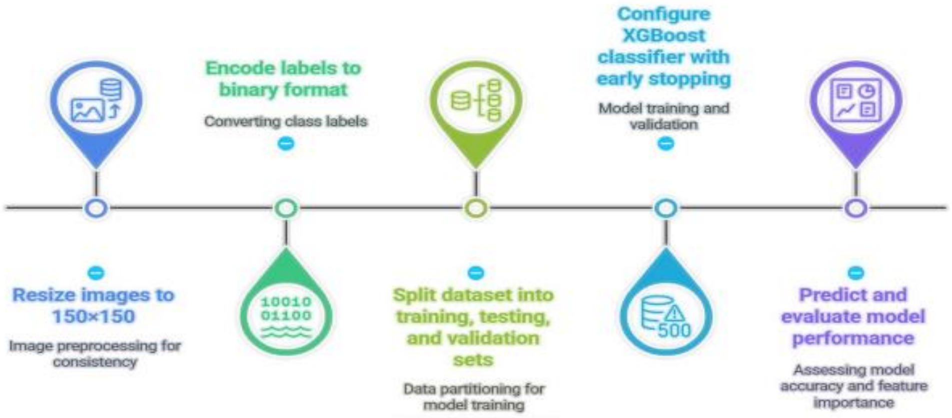


Figure 6. Workflow Model for XGBoost

III. XGBoost with PCA

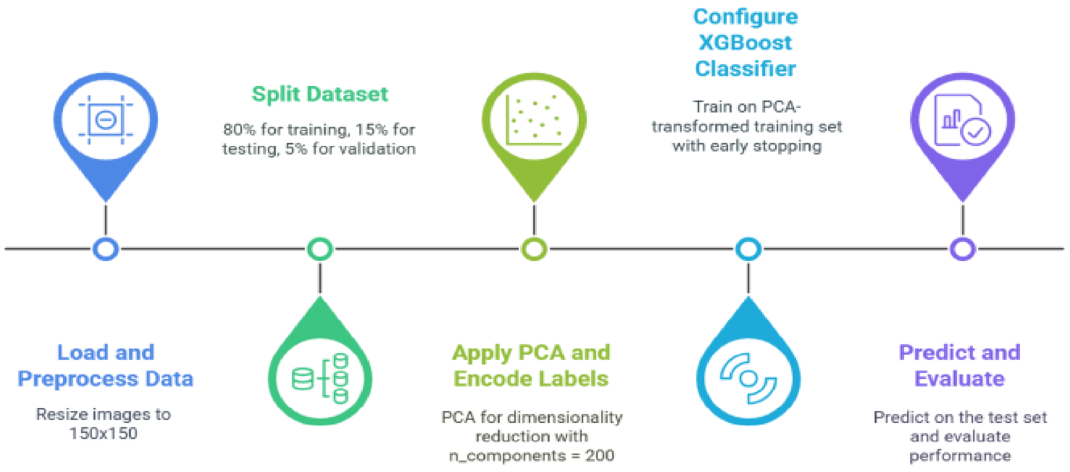


Figure 7. Workflow Model for XGBoost with PCA

B. Standalone DL - CNNs

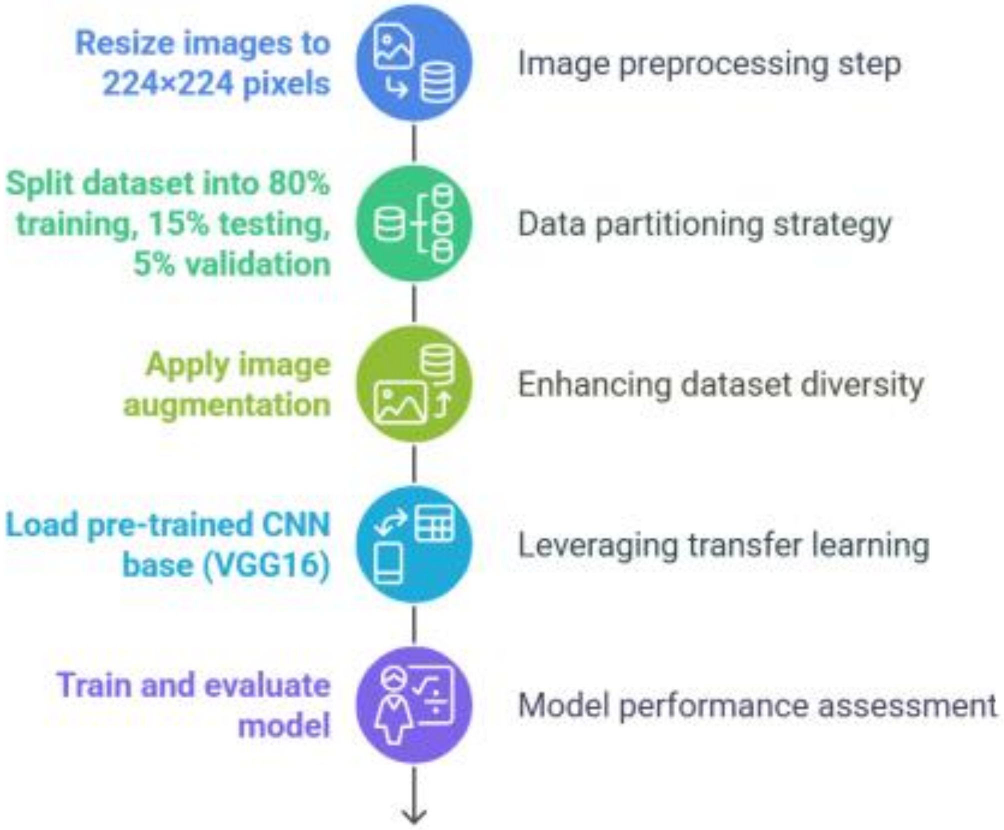


Figure 8. Workflow Model for CNNs

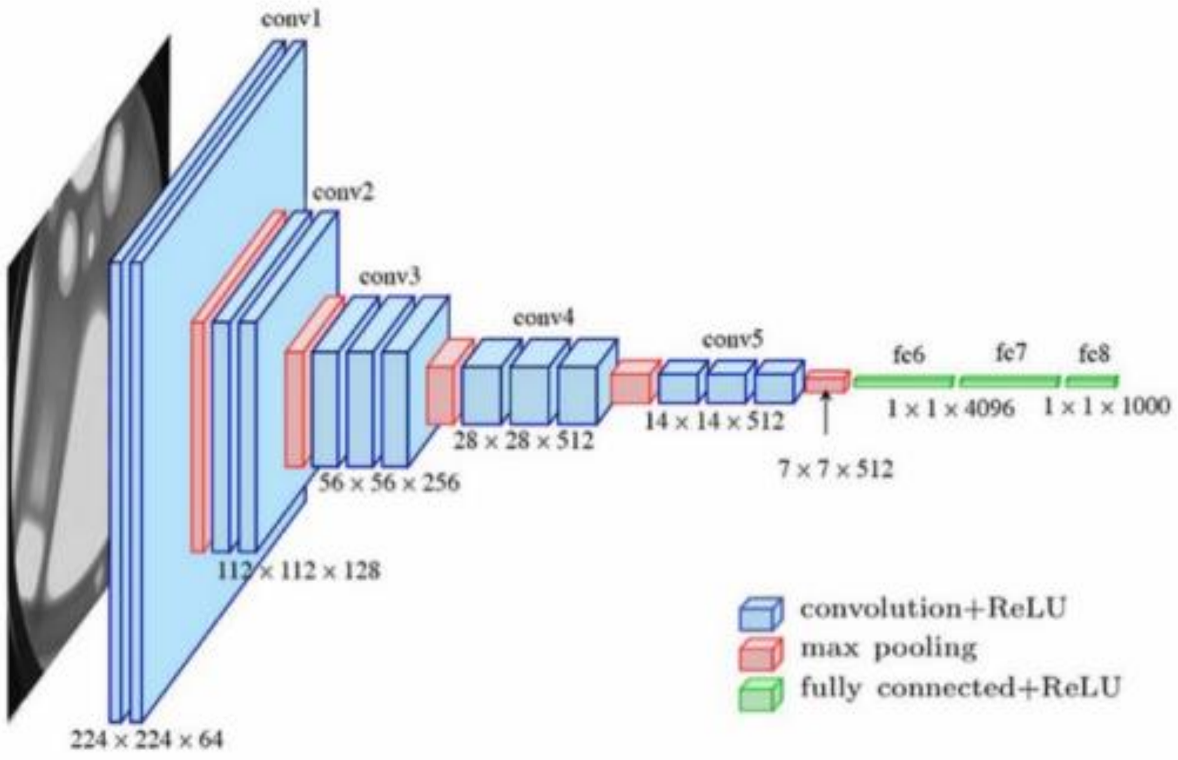


Figure 9: VGG Neural Network Architecture [20]

VGG16 is a deep convolutional neural network (CNN) architecture developed by the Visual Geometry Group at the University of Oxford; the “16” in its name refers to its 16 weight layers, which include 13 convolutional layers and 3 fully connected layers, making it one of the most influential models in image recognition and classification.

C. Hybrid ML and DL – XGBoost + CNNs

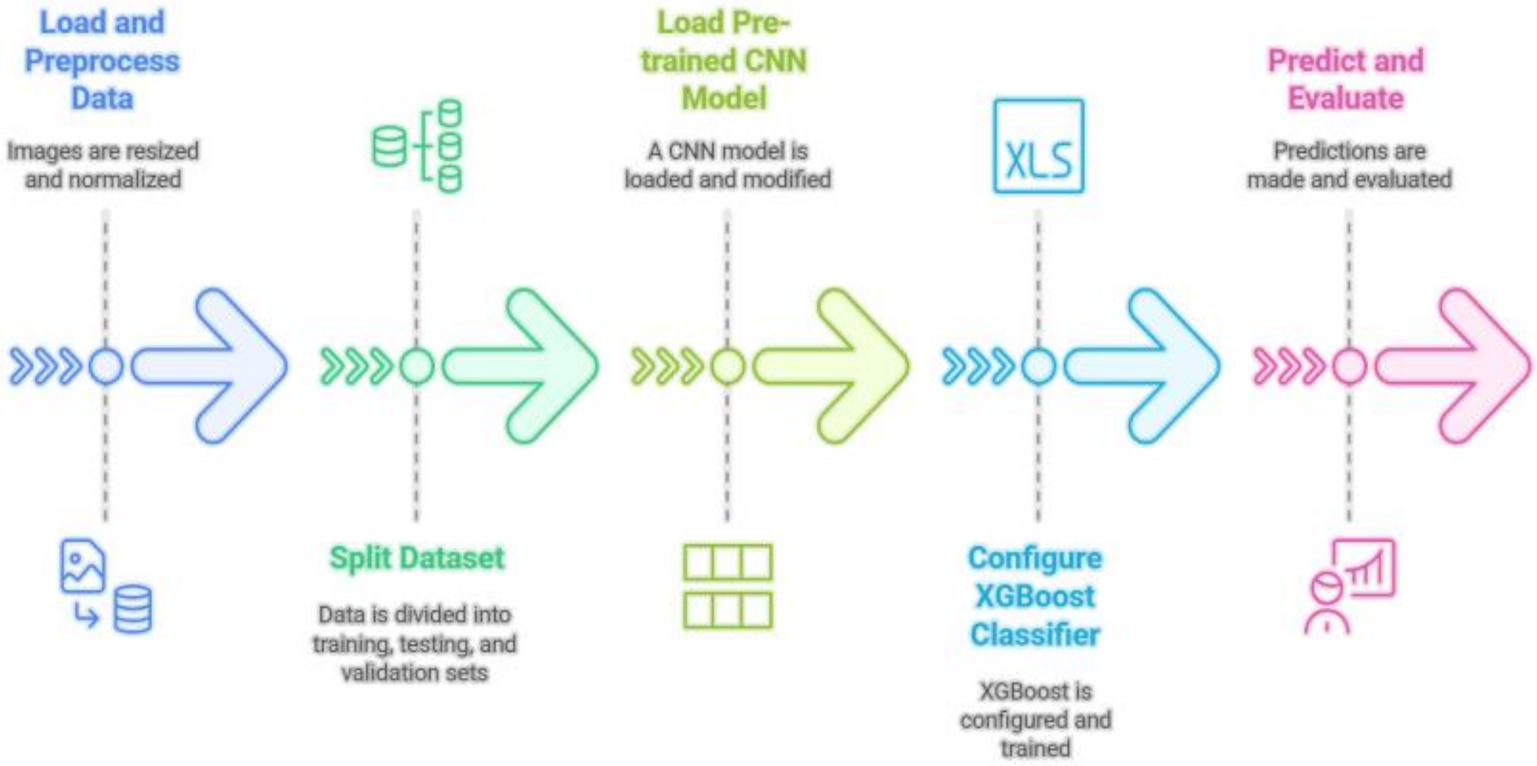


Figure 10. Workflow model for XGBoost with CNN

- This hybrid approach combines CNN-based feature extraction with XGBoost classification. A pre-trained CNN model, such as VGG16, is first used to extract high-level feature representations from chest X-ray images.
- Instead of using the CNN for final classification, the output feature maps from its final convolutional layer are flattened into one-dimensional vectors.
- These vectors are then used as inputs for an XGBoost classifier.

Method Type	Example Algorithms	Feature Extraction	Interpretability	Computational Cost	Training Time	Dataset Size Requirement
Isolated ML	SVM, XGBoost	Manual	High	Low/Moderate	Low to Moderate	Small to Moderate
Isolated DL	CNN	Automatic	Low	High	High	Large
Hybrid	CNN + SVM/XGBoost	Automatic + ML	Moderate	Moderate/High	Moderate to High	Moderate to Large

Table 1: Comparison of Machine Learning, Deep Learning, and Hybrid Approaches

- SVM (with and without PCA) performed acceptably when trained on 80% of data (83% test accuracy) but experienced steep declines as the training fraction fell.
- Transfer learning CNNs based on VGG16 maintained high accuracy (94% at 80% train and 90% at 20% train) and stable ROC-AUC (>0.90) across all splits, showing effective generalization. The last approach using VGG16 and
- XGBoost delivered the best performance (test accuracies of 96% in Brain MRI and 95% in chest X-ray) at all training splits. Moreover, its log-loss and error rates exhibited minimal sensitivity to reduced training size. These results prove that deep, pretrained feature representations offer the most effective solution for medical image classification when labelled data is limited.