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Kidney Stone Detection Using Machine Learning and Deep Learning

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Guided by:

Dr Achala Shakya

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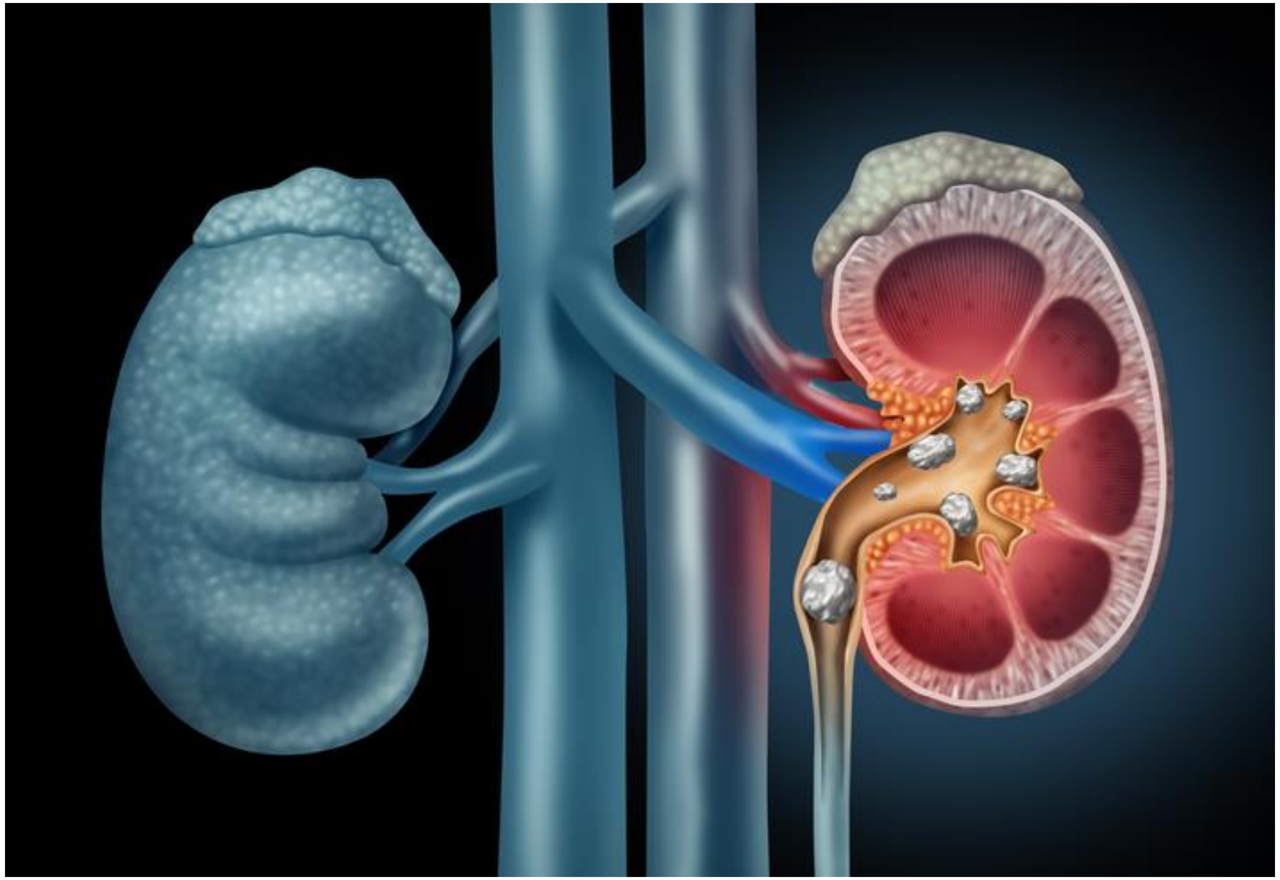
Abstract

This project leverages machine learning to detect kidney stones by classifying medical images into two categories: Normal (no stones) and Stone (presence of stones). Multiple models, including Random Forest, SVM, Logistic Regression, and Decision Tree, were implemented and evaluated. The goal is to identify the most accurate model, enhancing diagnostic accuracy and enabling efficient, automated kidney stone detection to improve patient care.



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Introduction

Kidney stones are a common yet painful medical condition, often requiring early detection for effective treatment. Traditional diagnostic methods, while reliable, can be time-consuming and dependent on manual interpretation. This project explores the potential of machine learning in revolutionizing kidney stone detection, utilizing advanced algorithms to classify medical images into Normal and Stone categories. By automating this critical diagnostic process, the project aims to reduce human error, enhance accuracy, and support timely medical interventions. Comparing models like Random Forest, SVM, Logistic Regression, and Decision Tree, this work identifies the most effective approach to build a robust, efficient solution for kidney stone diagnosis.

Problem Statement

Develop an advanced machine learning model to detect kidney stones from medical images, classified into two categories: Normal (no stones) and Stone (presence of stones). This solution aims to enhance diagnostic accuracy, streamline detection processes, and support healthcare professionals in providing timely and effective treatment for kidney stone patients.

Motivation

- **Prevalence of Kidney Stones:** Kidney stones are a growing global health concern, affecting millions of people annually. Timely detection is crucial to avoid complications and provide effective treatment, making early diagnosis a key priority.

- **Limitations of Traditional Methods:** Traditional methods of detecting kidney stones, such as physical examinations, X-rays, and CT scans, are often time-consuming, expensive, and reliant on human expertise. These methods may also involve long waiting times, which can delay critical treatment.

- **Potential of Machine Learning:** Machine learning algorithms can revolutionize kidney stone detection by automating the image classification process. With the ability to process vast amounts of medical images quickly, machine learning models can reduce human error and offer more consistent results.

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Objectives

Develop a Robust Classification Model: To create and train machine learning models that can accurately classify medical images of kidneys into two categories: Normal and Stone.

Evaluate Multiple Algorithms: To implement and evaluate the performance of various machine learning algorithms, such as Random Forest, Support Vector Machine (SVM), Logistic Regression, and Decision Tree, in terms of accuracy, precision, and recall.

Optimize Model Performance: To fine-tune the chosen models for optimal performance using techniques like hyperparameter tuning and cross-validation to ensure the highest possible accuracy in kidney stone detection.

Automate the Detection Process: To build an automated system that can process medical images and provide real-time predictions, reducing manual intervention and enhancing diagnostic speed.

Literature Review

S. No.	Authors	Title	Journal/Conference	Year	Key Focus	Major Findings
1	Saman Ebrahimi, Vladimir Y. Mariano	Image Quality Improvement in Kidney Stone Detection on Computed Tomography [1]	Journal of Image and Graphics	2015	Image quality improvement in kidney stone detection on CT images	Enhanced image quality led to better detection accuracy of kidney stones.
2	Prema T. Akkasaligar, Sunanda Biradar, Veena Kumbar	Kidney Stone Detection in Computed Tomography Images [2]	IEEE	2017	Kidney stone detection using CT images	Proposed techniques showed significant improvement in detecting kidney stones from CT scans.
3	Aniket Gaikwad, Azharuddin Inamdar, Vikas Behera	Lung Cancer Detection Using Digital Image Processing on CT Scan Images [3]	International Research Journal of Engineering and Technology	2016	Application of digital image processing for lung cancer detection in CT images	Effective preprocessing and segmentation methods improved detection accuracy for lung cancer.
4	Brisbane Wayne, R. Bailey Michael, D. Sorensen Mathew	An Overview of Kidney Stone Imaging Techniques [4]	Nature Reviews Urology	2016	Comparative analysis of kidney stone imaging methods	Detailed review of various imaging techniques like CT, ultrasound, and MRI for kidney stone diagnosis.

Table 1 Literature Review

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Literature Review

S. No.	Authors	Title	Journal/Conference	Year	Key Focus	Major Findings
5	S. Asadi, H. Hassanpour, A. Pouyan	Texture-Based Image Enhancement Using Gamma Correction [5]	Middle-East Journal of Scientific Research	2010	Enhancing image textures using gamma correction	Improved visibility of medical images using gamma correction for texture-based image enhancement.
6	R. C. Gonzalez, R. E. Woods	Digital Image Processing [6]	Book	1992	Fundamentals of digital image processing	Introduced foundational concepts and algorithms in digital image processing.
7	D. Y. Kim, J. W. Park	Computer-Aided Detection of Kidney Tumor on Abdominal CT Scans [7]	Acta Radiologica	2004	Computer-aided detection of kidney tumors	Achieved improved tumor localization using computer-aided techniques.
8	D. T. Lin, C. C. Lei, S. W. Hung	Computer-Aided Kidney Segmentation on Abdominal CT Images [8]	IEEE Transactions on Information Technology in Biomedicine	2006	Automated kidney segmentation in CT images	Presented a reliable algorithm for segmenting kidneys in CT scans.
9	F. L. Coe, A. Evan, E. Worcester	Kidney Stone Disease [9]	Journal of Clinical Investigation	2005	Overview of kidney stone disease	Explored causes, prevention, and treatments for kidney stones.

Table 1 Literature Review

Literature Review

S. No.	Authors	Title	Journal/Conference	Year	Key Focus	Major Findings
10	F. Grases, A. Costa-Bauza, R. M. Prieto	Renal Lithiasis and Nutrition[10]	Nutrition Journal	2006	Role of nutrition in kidney stone formation	Found a significant relationship between dietary factors and kidney stone formation.
11	Sri Madhava Raja N, Rajinikanth V, Latha K	Otsu-Based Optimal Multilevel Image Thresholding Using Firefly Algorithm[11]	Modelling and Simulation in Engineering	2014	Image thresholding for segmentation	Proposed a firefly algorithm-based method for efficient image thresholding.
12	R. Vishnupriya, N. Sri Madhava Raja, V. Rajinikanth	An Efficient Clustering Technique and Analysis of Infrared Thermograms [12]	International Conference on Biosignals Images and Instrumentation	2017	Clustering analysis of infrared thermograms	Developed an efficient clustering method for thermal imaging analysis.
13	N. Sri Madhava Raja, S. L. Fernandes, Nilanjan Dev, S. Chandra Satapathy, V. Rajinikanth	Contrast-Enhanced Medical MRI Evaluation Using Tsallis Entropy and Region Growing Segmentation[13]	Journal of Ambient Intelligence and Humanized Computing	2018	MRI image evaluation using contrast enhancement	Applied Tsallis entropy for better segmentation and evaluation of medical MRI images.
14	N. S. M. Raja, P. R. V. Lakshmi, K. P. Gunasekaran	Firefly Algorithm-Assisted Segmentation of Brain Regions Using Tsallis Entropy and Markov Random Field[14]	Lecture Notes in Networks and Systems	2018	Brain region segmentation using firefly algorithm	Improved brain region segmentation in MRI images using entropy and Markov Random Field models.

Table 1 Literature Review

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Data Analysis – Labels Distribution

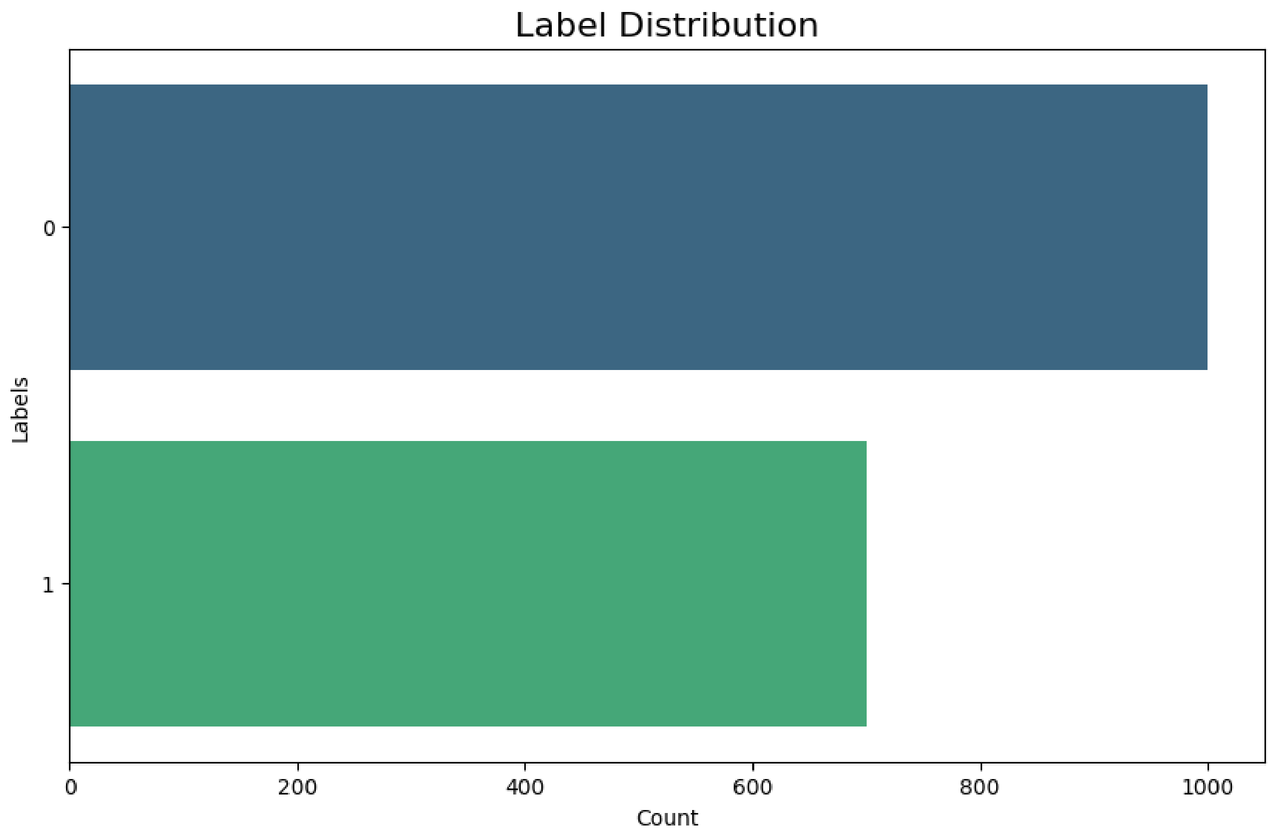

Fig. 1 Label Distribution

1. Fig. 1 shows the distribution of each label as per their image count.
2. Label 0 represents there is no kidney stone present.
3. Label 1 represents there is kidney stone present.
4. Label 0: 1000 images
   Label 1: 700 images

Data Analysis – Heatmap of Label Count

Fig. 2 Heatmap of Label Count

Data Analysis – Label Proportions

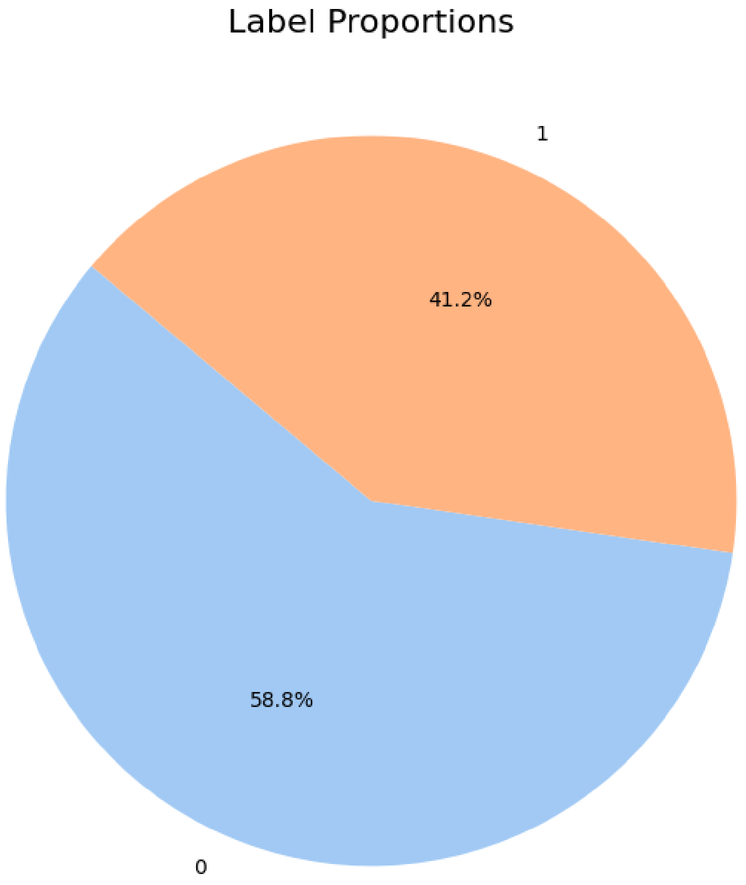

Fig. 3 Label Proportions

1. Fig. 3 shows the proportions of each label as per their image count.
2. Label 0 represents there is no kidney stone present.
3. Label 1 represents there is kidney stone present.
4. Label 0: 58.8%
Label 1: 41.2%

Data Analysis – Example Images

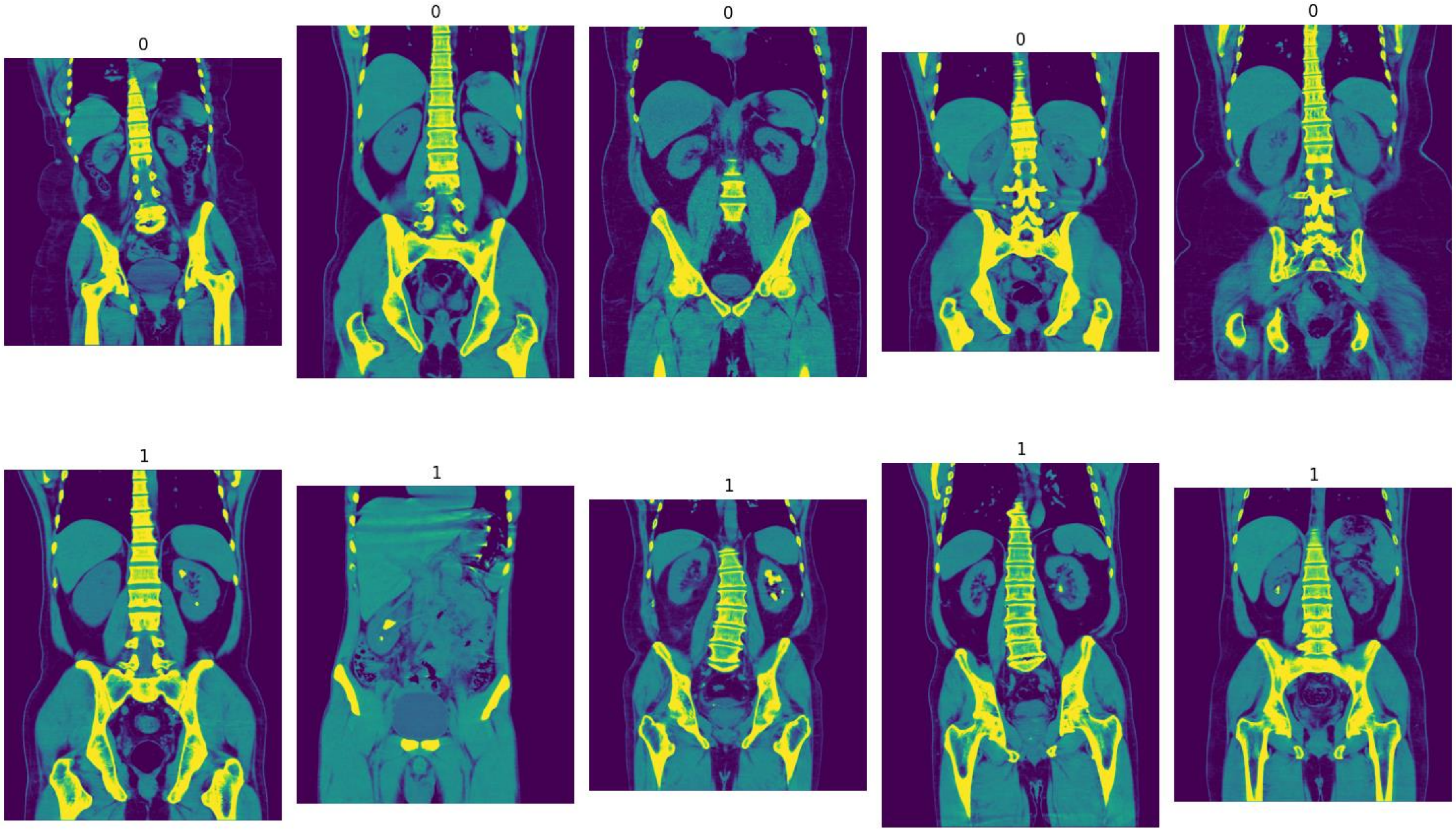

Fig. 4 Example Images

Machine Learning

- Data-Driven Decision Making: Machine learning models help in analyzing large datasets to identify patterns and make informed predictions.

- Automation of Complex Tasks: These models automate tasks that traditionally require human intervention, improving efficiency and accuracy.

- Improved Accuracy: Machine learning models continually learn from data, leading to improved prediction accuracy over time.

- Versatility in Applications: From image recognition to medical diagnoses, machine learning models can be applied across a wide range of industries and domains.

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Logistic Regression

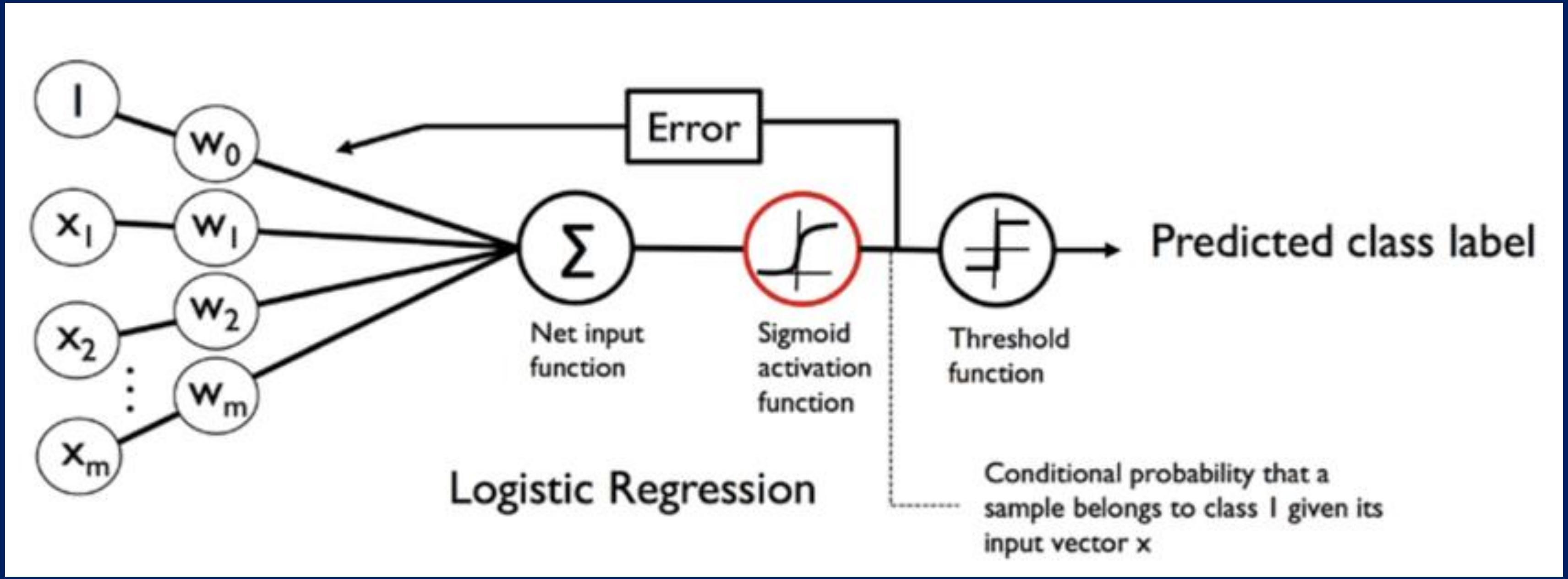

Fig. 5 Logistic Regression Architecture [15]

1. Binary Classification: Logistic regression is commonly used for binary classification tasks, predicting outcomes like "yes/no" or "true/false".

2. Probability Estimation: It estimates the probability of a given input belonging to a certain class, providing a score between 0 and 1.

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Logistic Regression

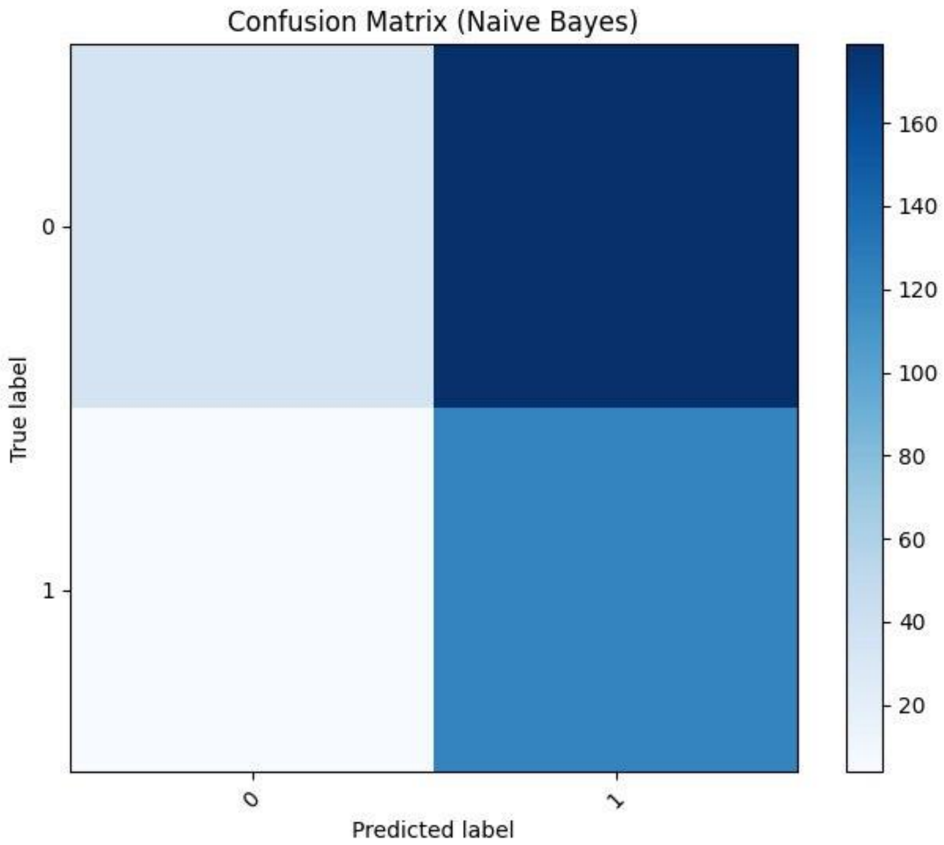

Fig. 6 Confusion Matrix
for Naïve Bayes

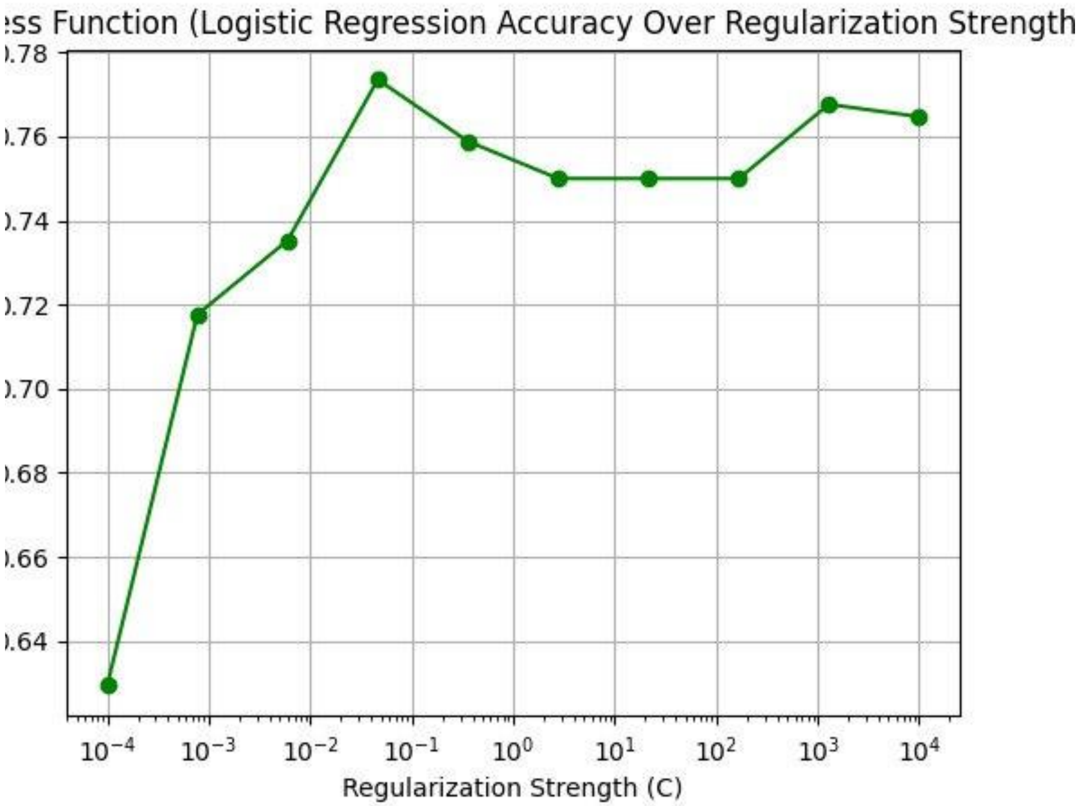

Fig. 7 Fitness Function
for Logistic Regression

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Logistic Regression

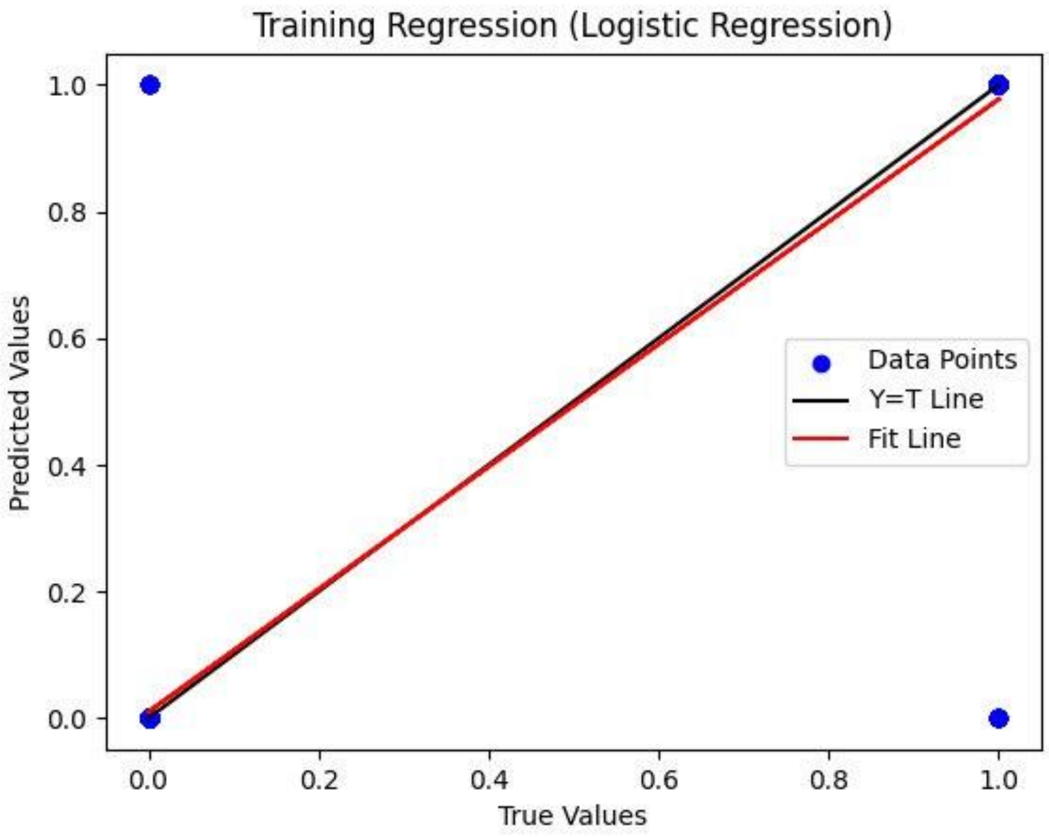

Fig. 8 Training Regression for Logistic Regression

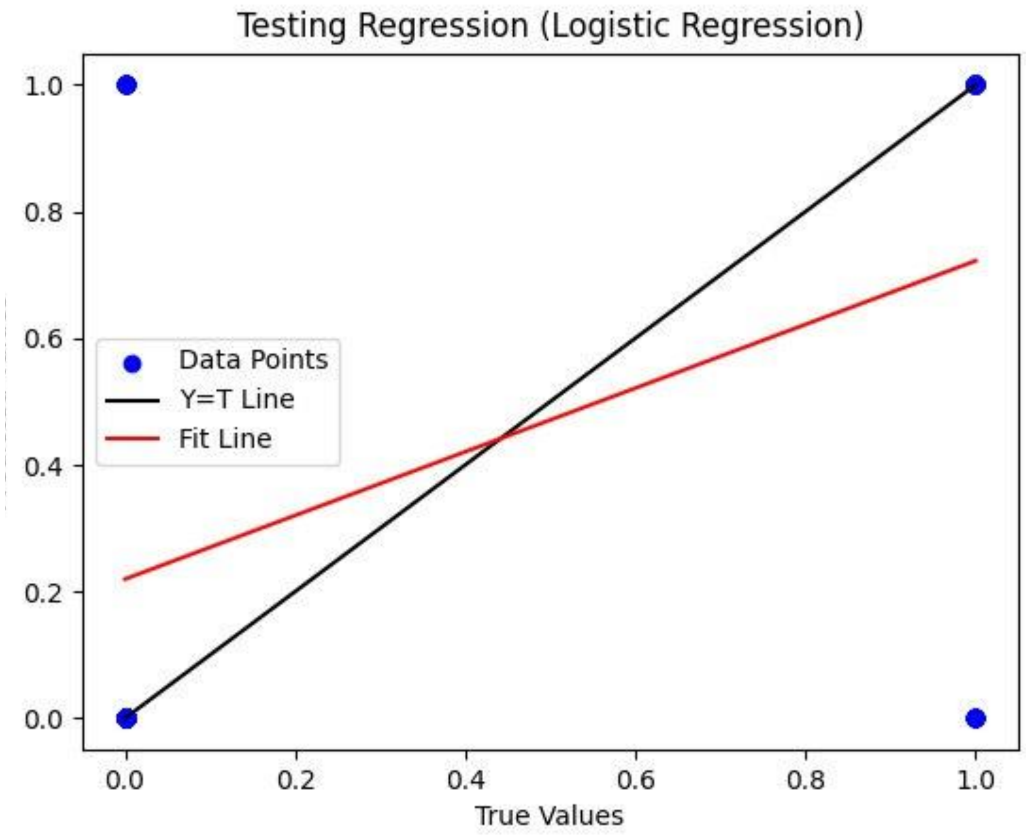

Fig. 9 Testing Regression for Logistic Regression

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Logistic Regression: Evaluation Metrics

Metric	Value
Accuracy	0.758823529411765
Precision	0.7430764815612
Recall	0.751298026998962
F1 Score	0.746139277389277

Fig. 10 Evaluation Metrics
for Logistic Regression

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Naïve Bayes

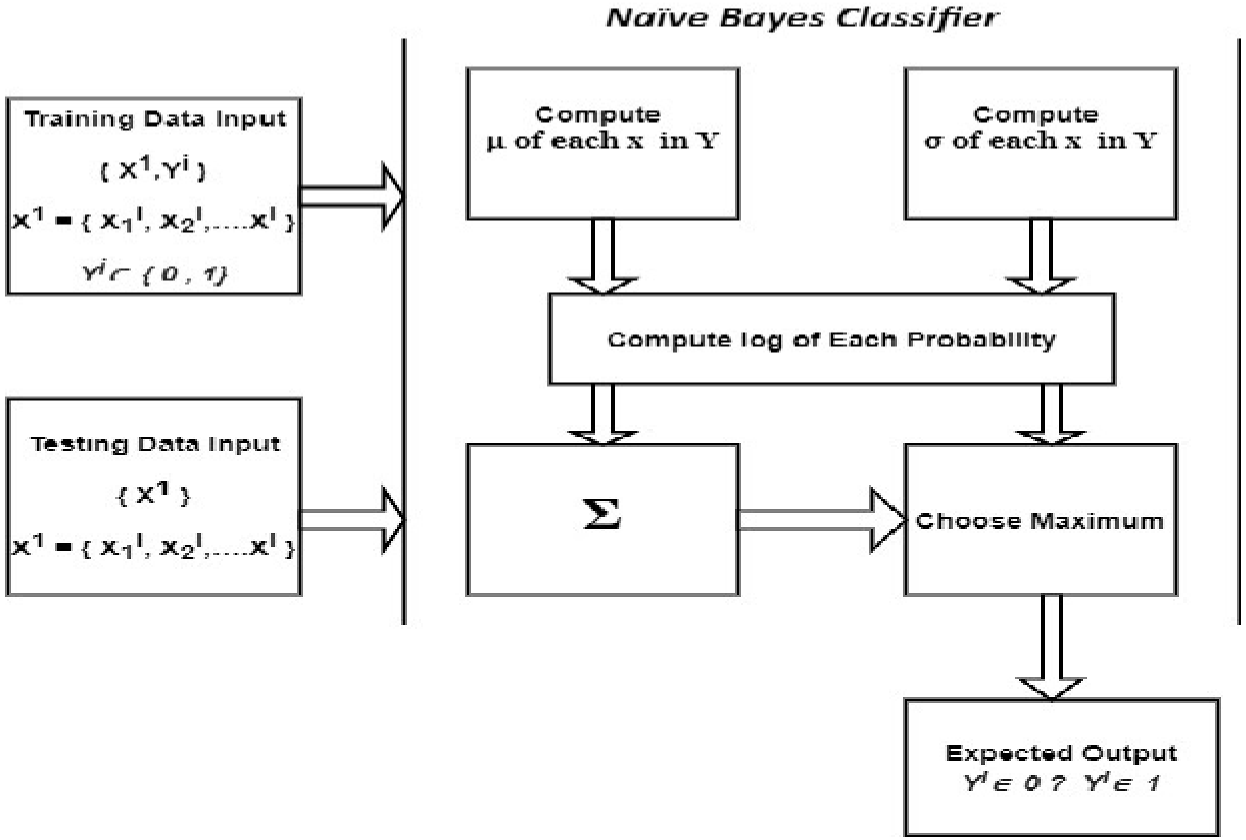

Fig. 11 Naïve Bayes Architecture [16]

1. Probabilistic: Uses Bayes' theorem fo classification.
2. Independence Assumption: Assumes feature independence.
3. Efficient: Fast and scalable for large datasets.
4. Common Applications: Used in text classification and medical predictions

Naïve Bayes

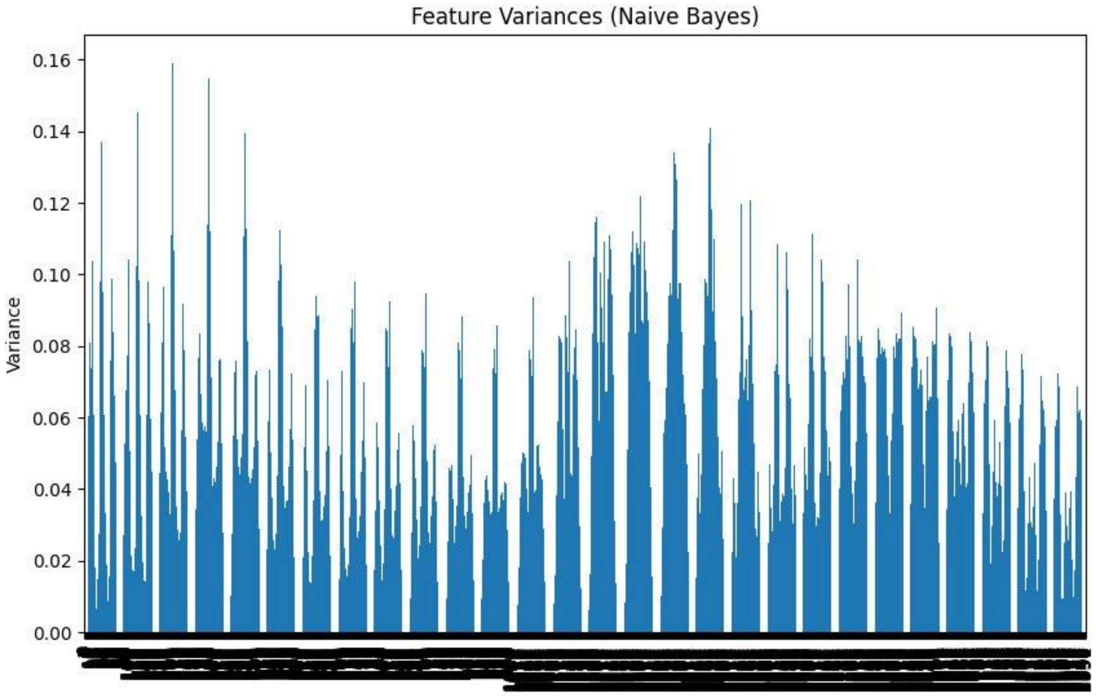

Fig. 12 Feature Variances
for Naïve Bayes

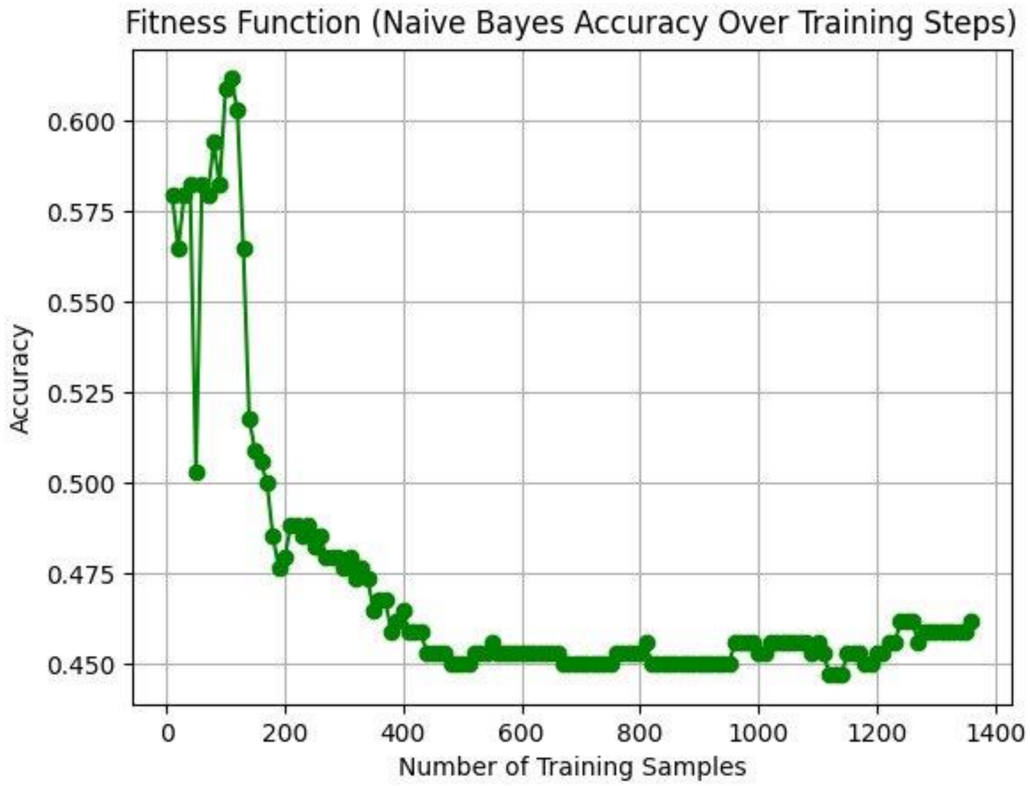

Fig. 13 Fitness Function
for Naïve Bayes

Naïve Bayes

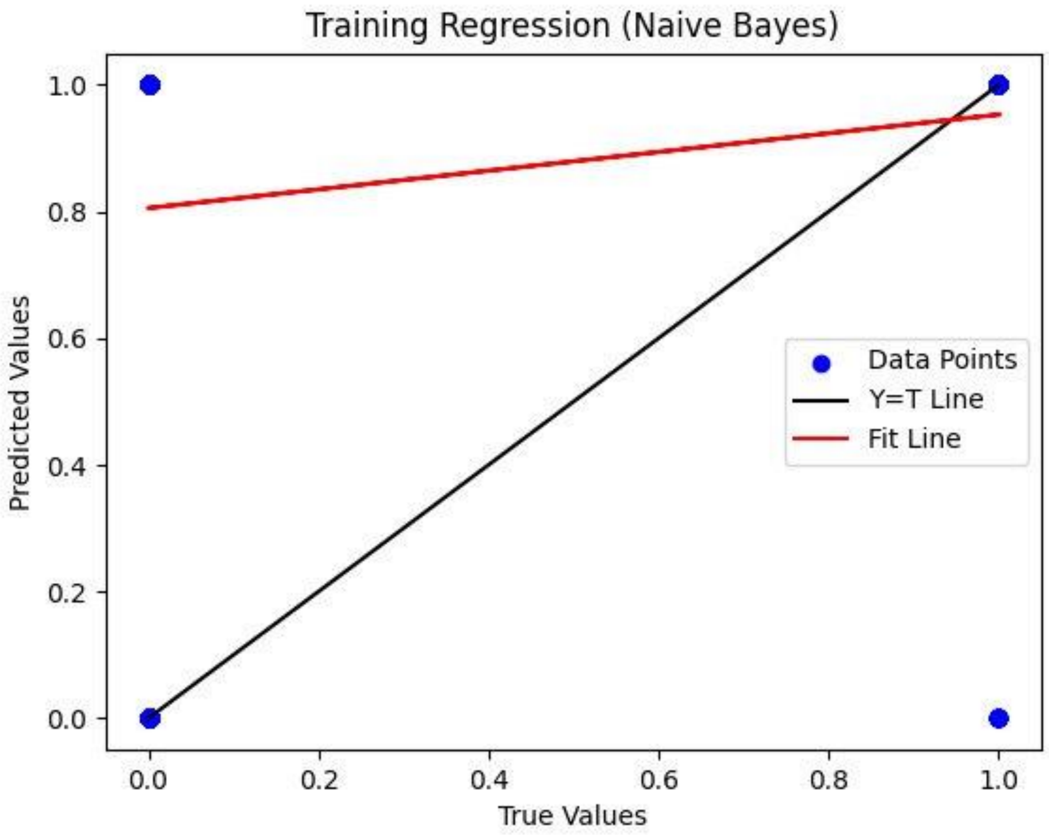

Fig. 14 Training Regression for Naïve Bayes

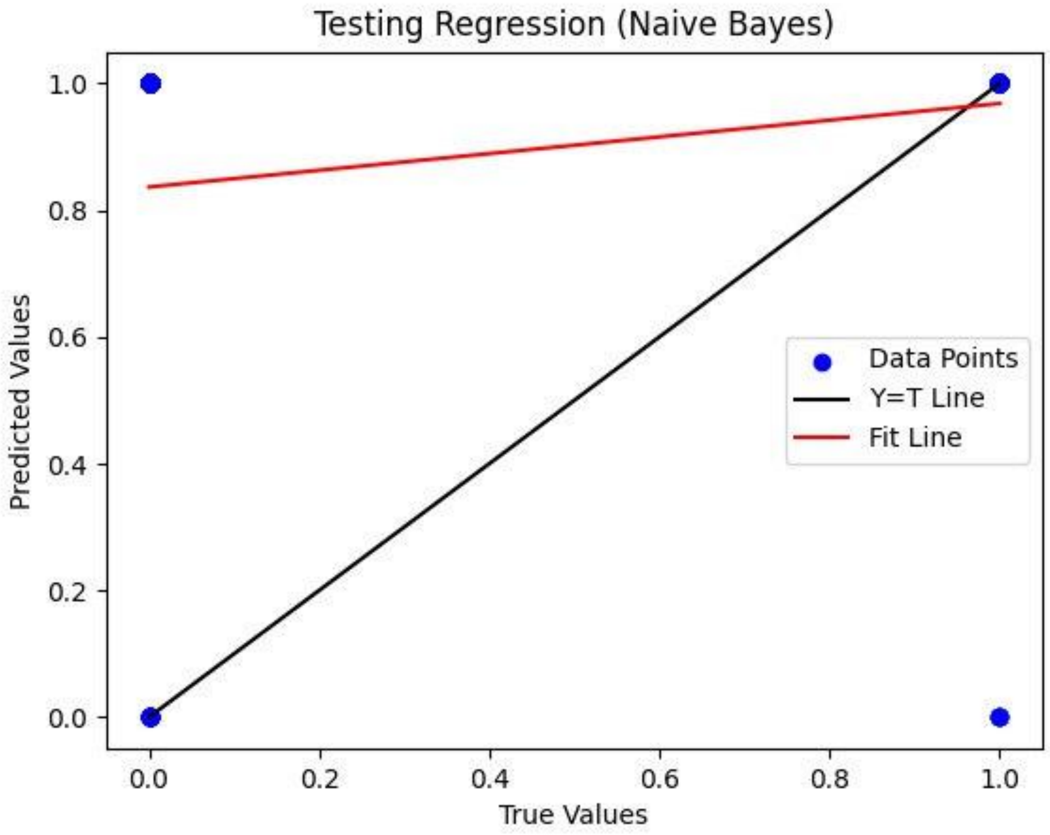

Fig. 15 Testing Regression for Naïve Bayes

Naïve Bayes: Evaluation Metrics

Metric	Value
Accuracy	0.461764705882353
Precision	0.651375756026919
Recall	0.565902685061564
F1 Score	0.424054206662902

Fig. 16 Evaluation Metrics
for Naïve Bayes

K Nearest Neighbor

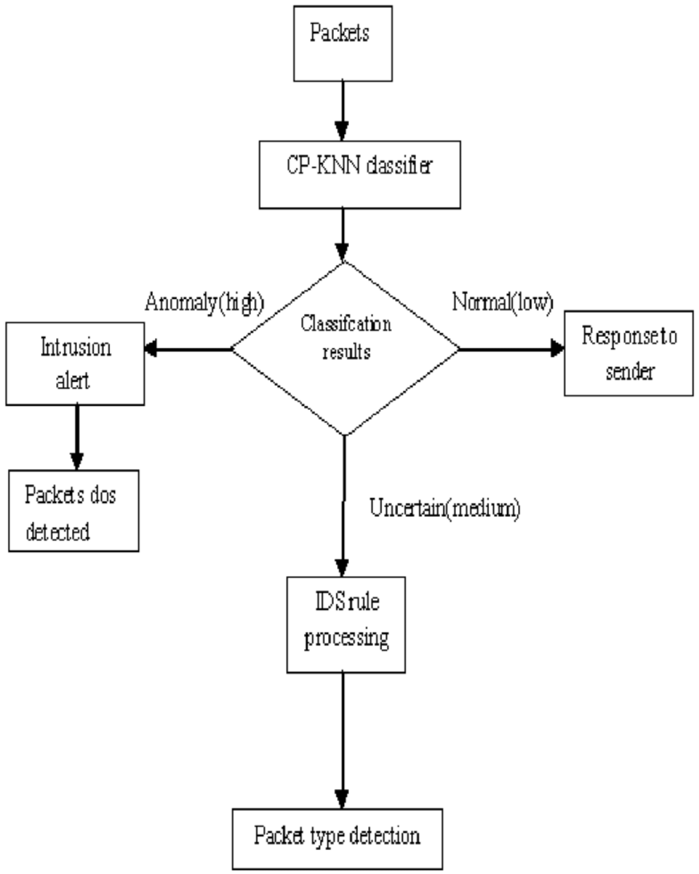

Fig. 17 KNN Architecture [17]

1. Instance-based: Classifies based on nearest data points.
2. Non-parametric: No assumptions about data distribution.
3. Simple: Easy to understand and implement.
4. Flexible: Works for both classification and regression tasks.

K Nearest Neighbor

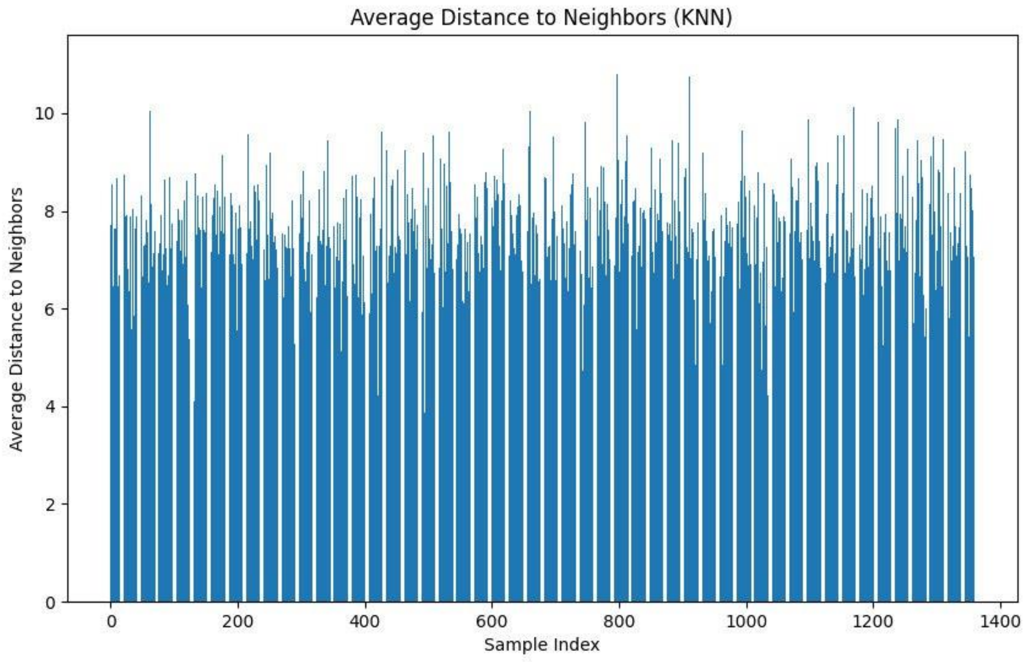

Fig. 18 Average Distance to Neighbors for KNN

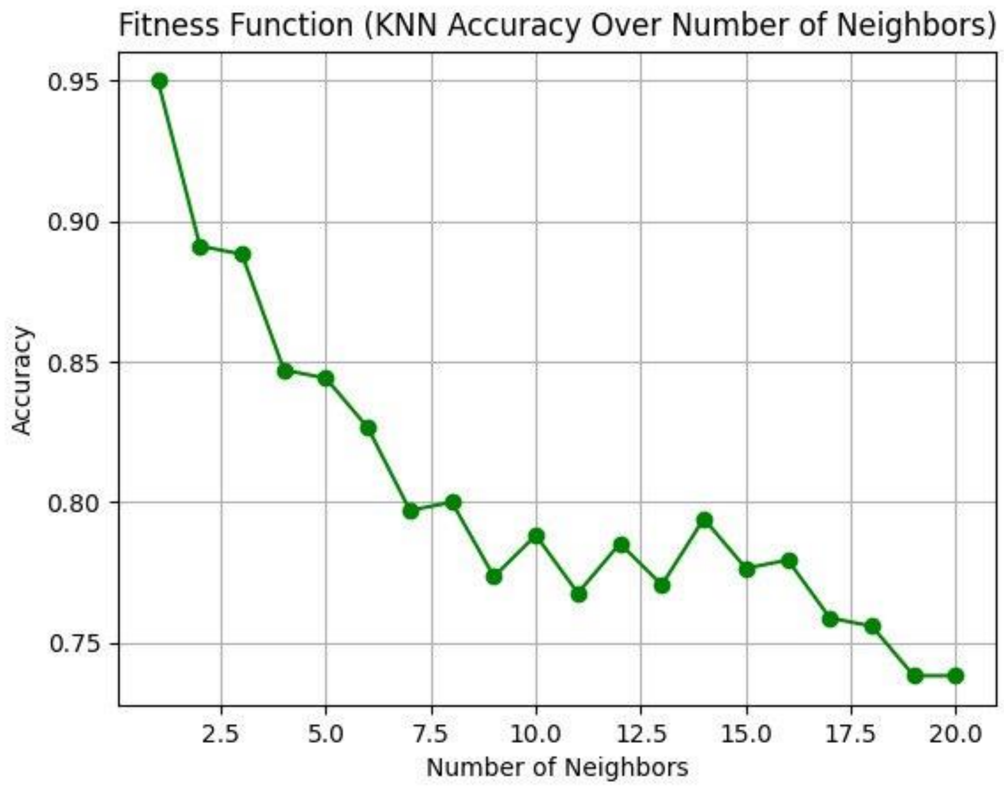

Fig. 19 Fitness Function for KNN

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K Nearest Neighbor

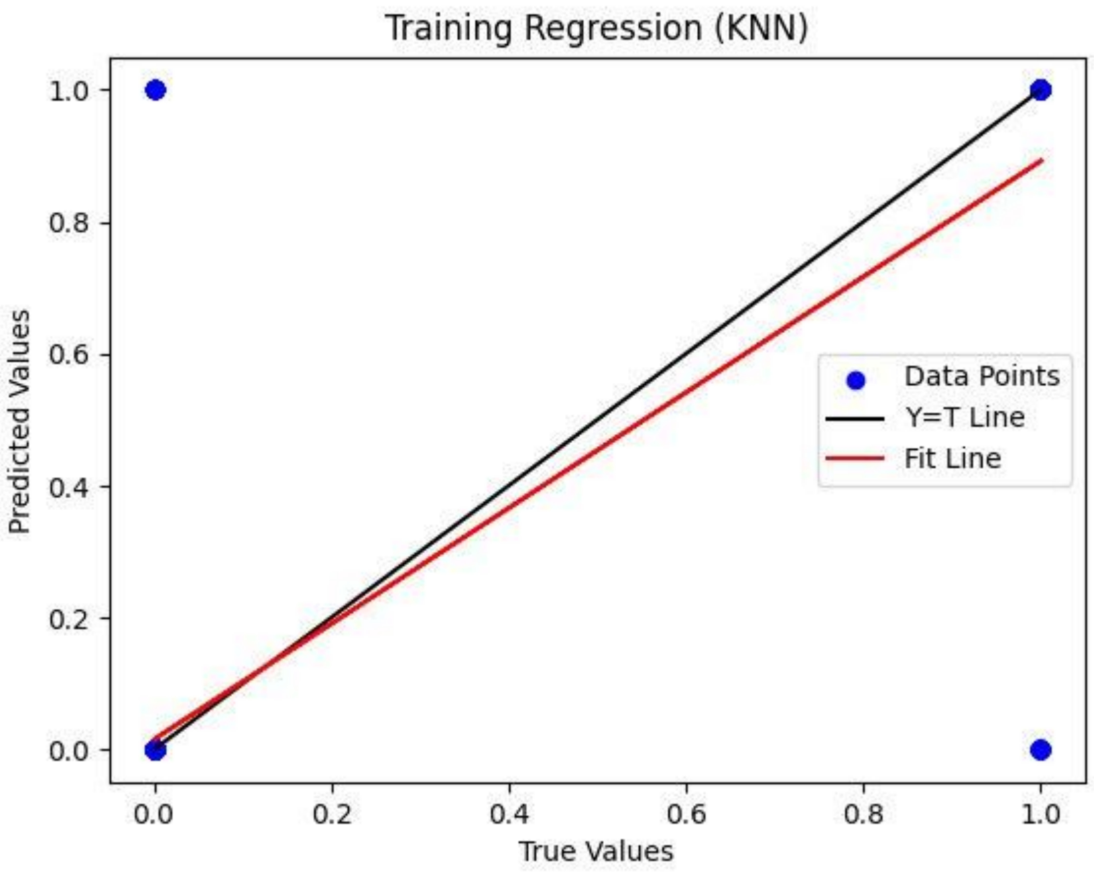

Fig. 20 Training Regression for KNN

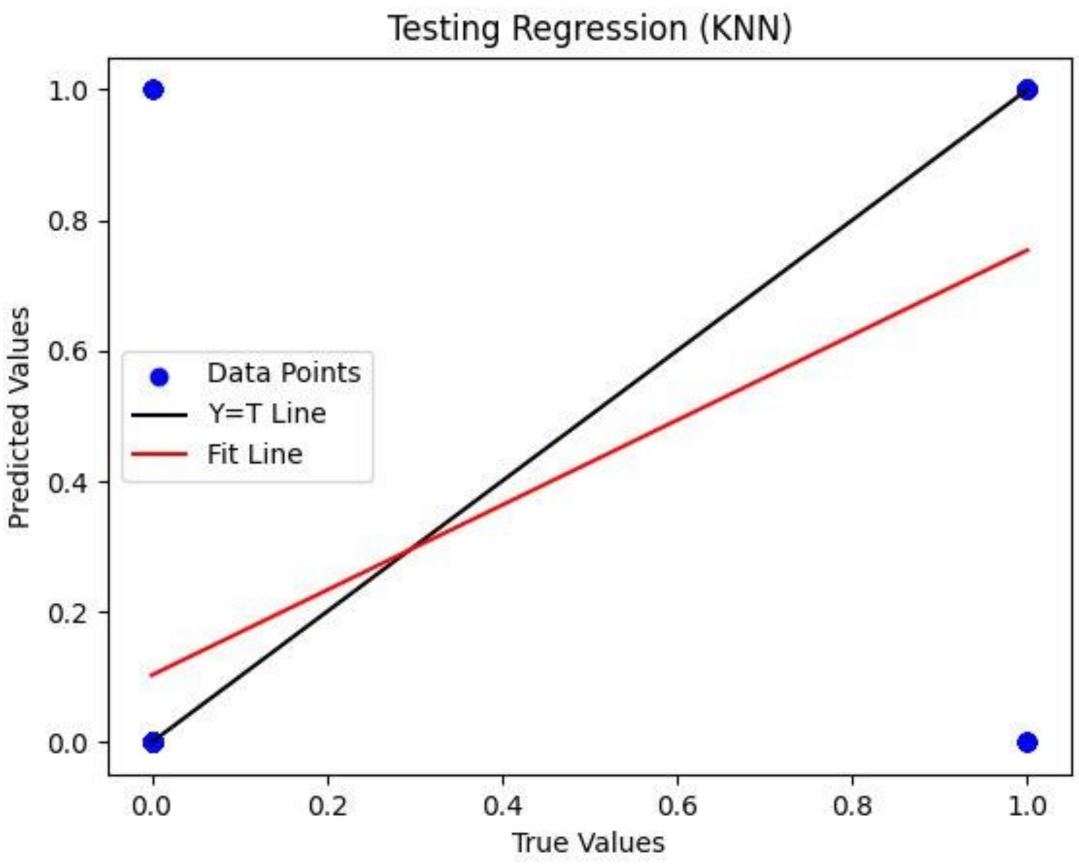

Fig. 21 Testing Regression for KNN

K Nearest Neighbor: Evaluation Metrics

Metric	Value
Accuracy	0.844117647058824
Precision	0.836476179525507
Recall	0.825582257825249
F1 Score	0.830305769792167

Fig. 22 Evaluation Metrics for KNN

Support Vector Machine

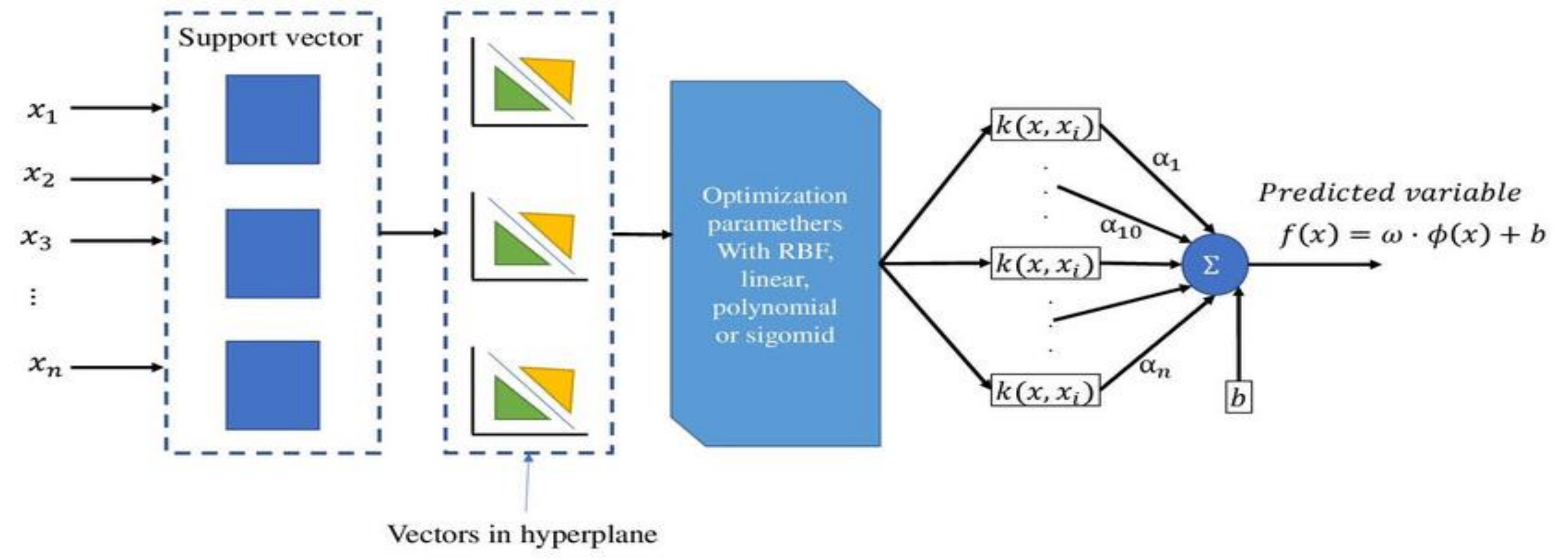

Fig. 23 SVM Architecture [18]

1. Margin Maximization: SVM finds the optimal hyperplane that maximizes the margin between classes.
2. Effective for High Dimensions: Works well in high-dimensional spaces.

Support Vector Machine

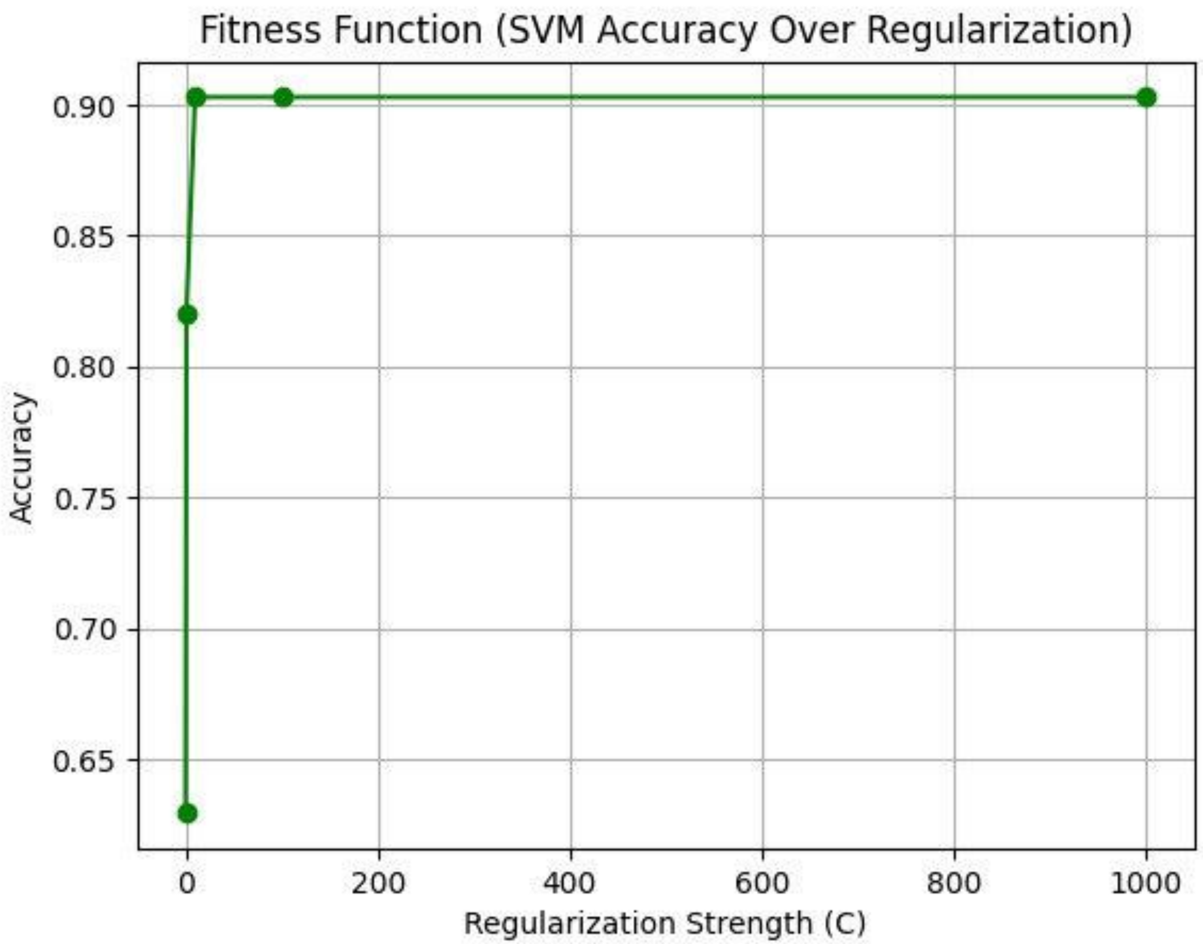

Fig. 24 Fitness Function for SVM

Support Vector Machine

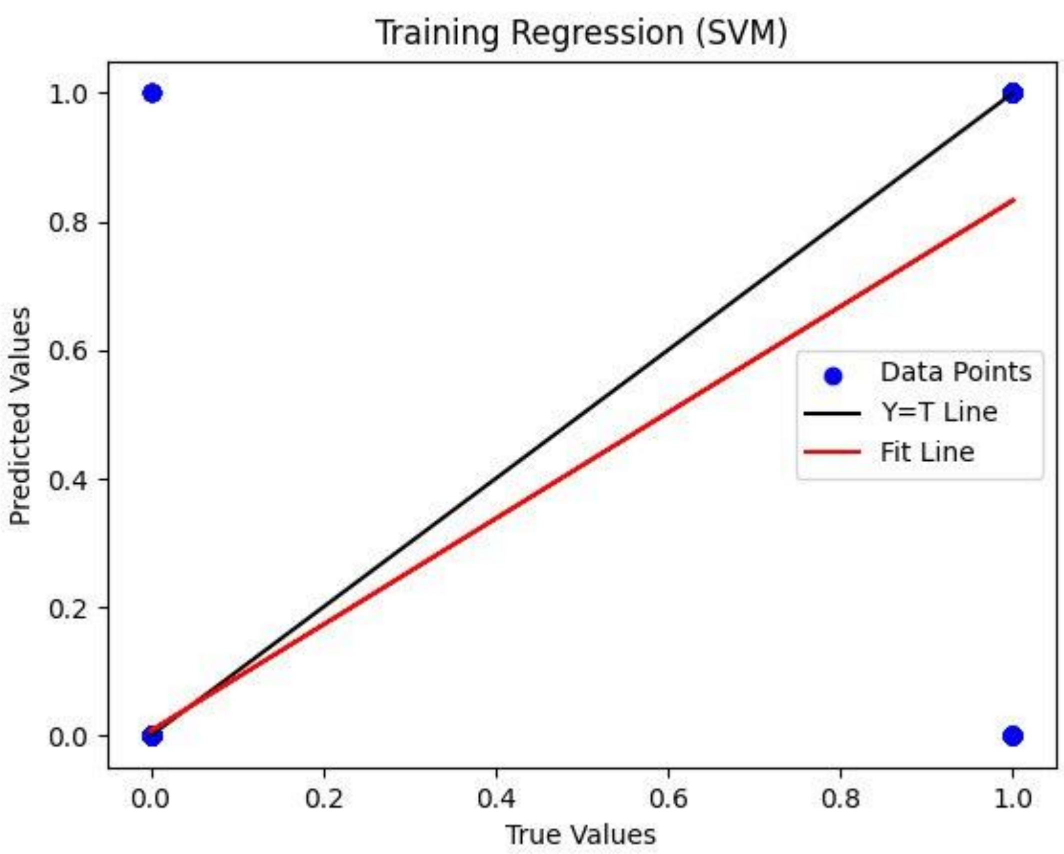

Fig. 25 Training Regression for SVM

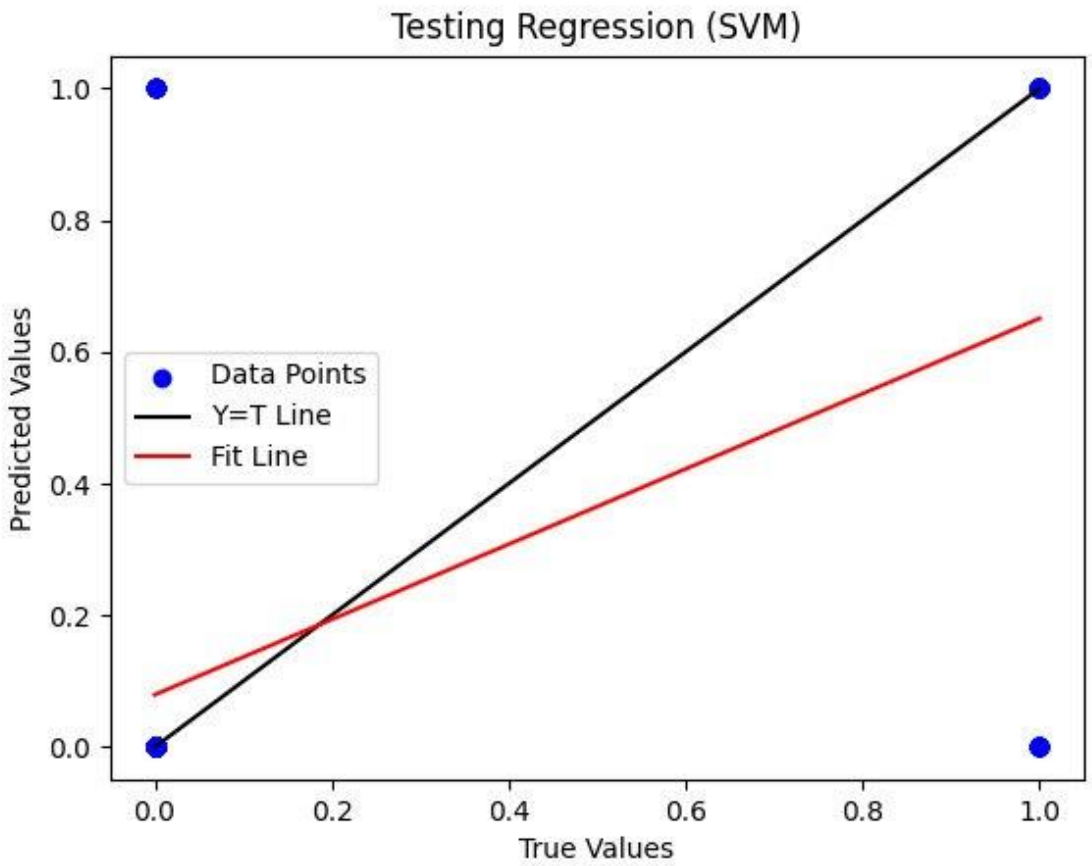

Fig. 26 Testing Regression for SVM

Support Vector Machine: Evaluation Metrics

Metric	Value
Accuracy	0.820588235294118
Precision	0.822855107087472
Recall	0.785677199228601
F1 Score	0.797411477411477

Fig. 27 Evaluation Metrics for SVM

Decision Tree

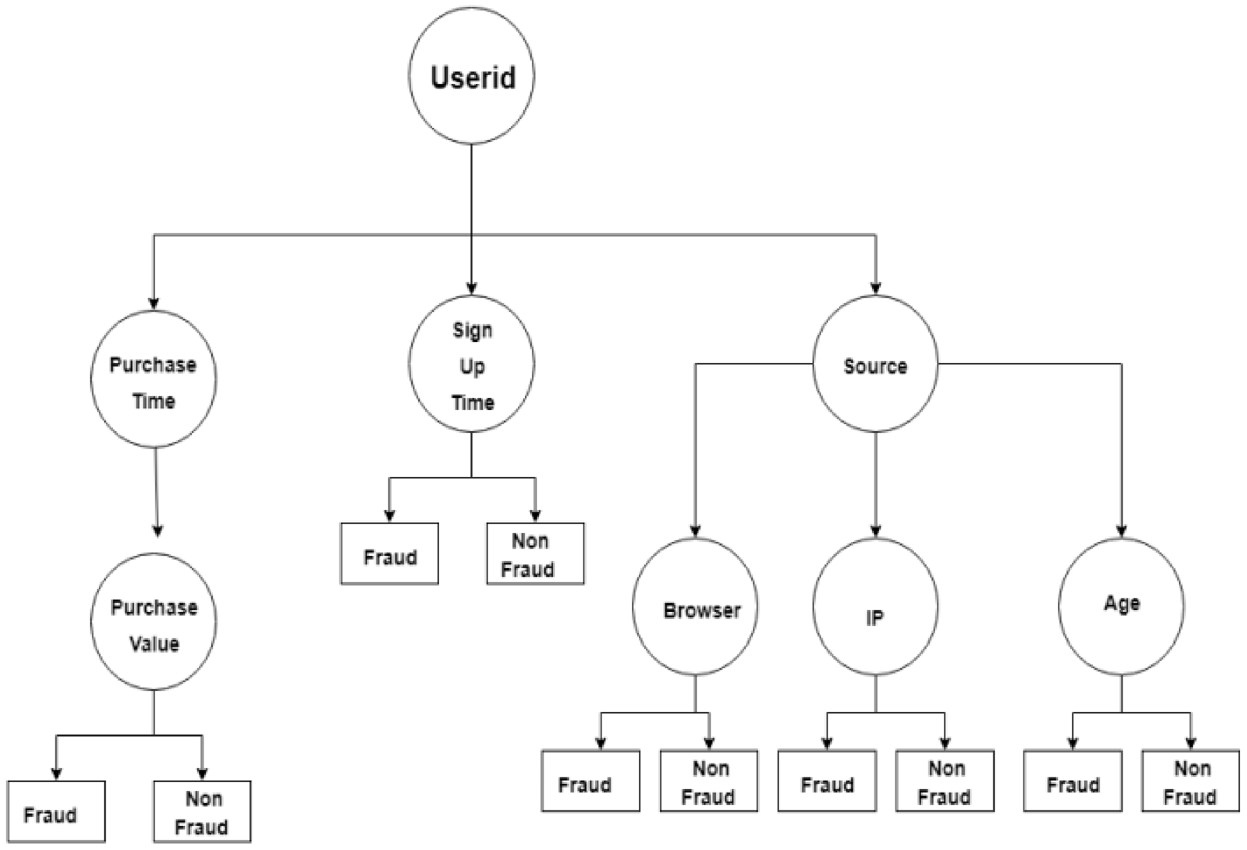

Fig. 28 DT Architecture[19]

1. Tree Structure: Splits data based on feature values.
2. Interpretable: Easy to understand and visualize.
3. Handles Both Data Types: Works with numerical and categorical data.
4. Overfitting Risk: Prone to overfitting, but can be controlled.

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Decision Tree

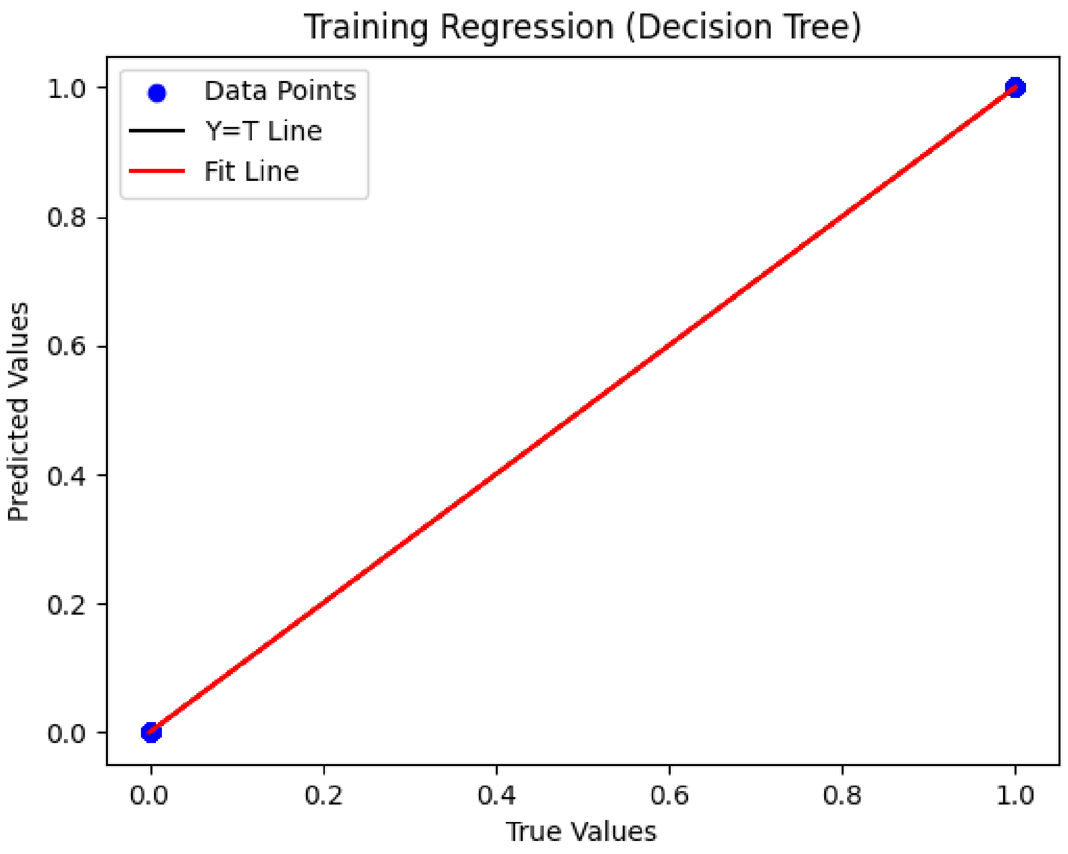

Fig. 29 Training Regression for DT

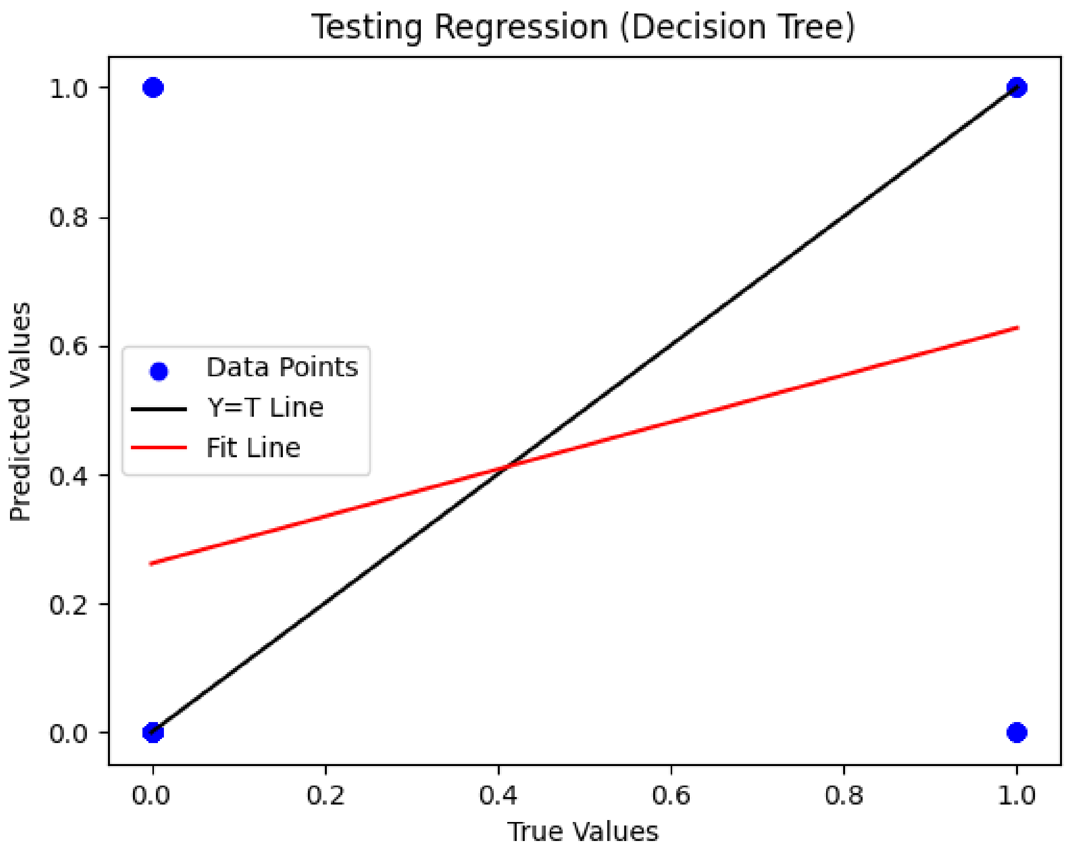

Fig. 30 Testing Regression for DT

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Decision Tree: Evaluation Metrics

Metric	Value
Accuracy	0.697058823529412
Precision	0.677958446251129
Recall	0.682650941996736
F1 Score	0.679770297826425

Fig. 31 Evaluation Metrics for DT

Random Forest

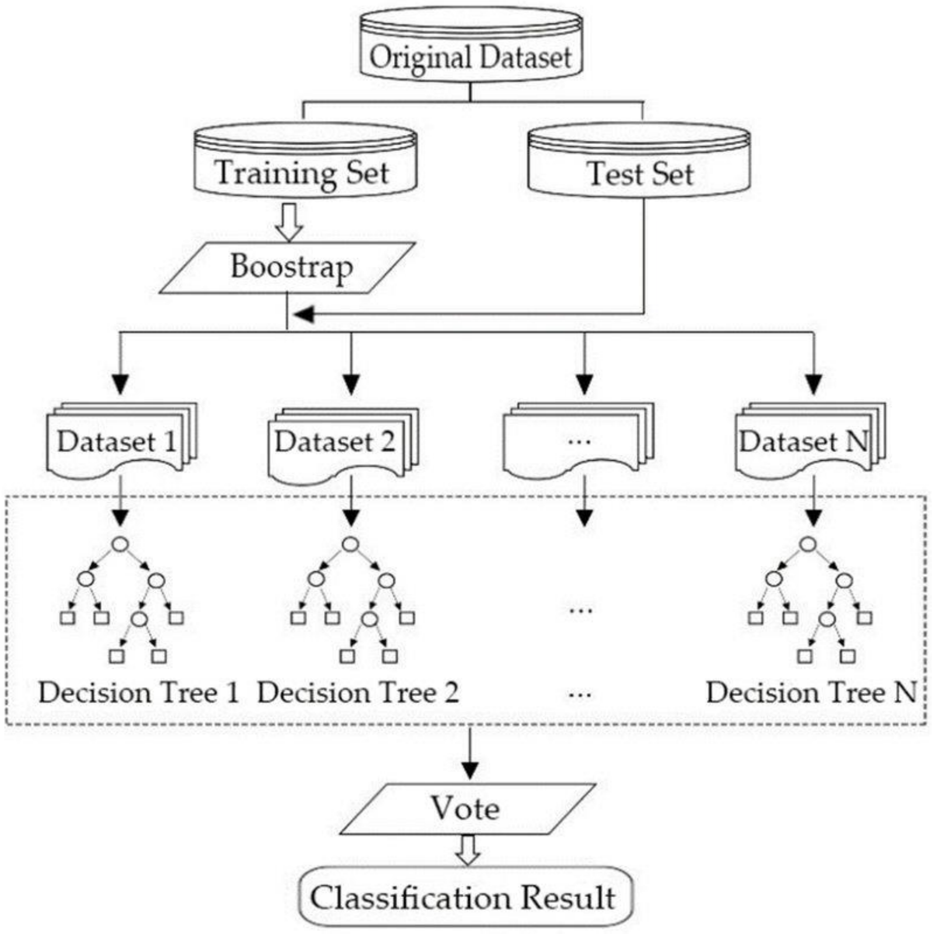

Fig. 32 Random Forest Architecture [20]

1. Combines multiple decision trees for better accuracy.
2. Versatile: Handles both classification and regression tasks.
3. Robust: Reduces overfitting compared to single trees.
4. Feature Importance: Highlights key features influencing predictions.

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Random Forest

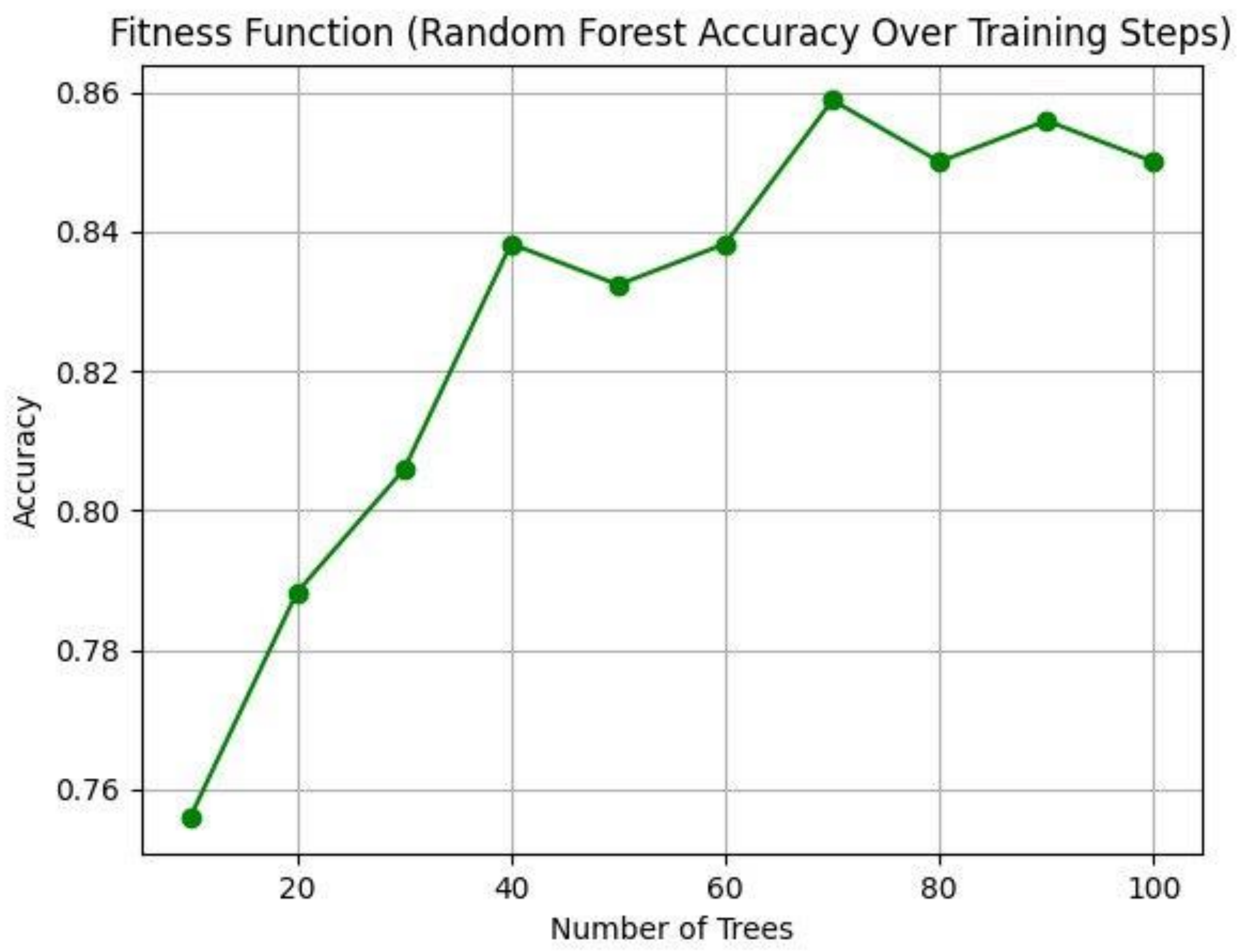

Fig. 33 Fitness Function
for Random Forest

Random Forest

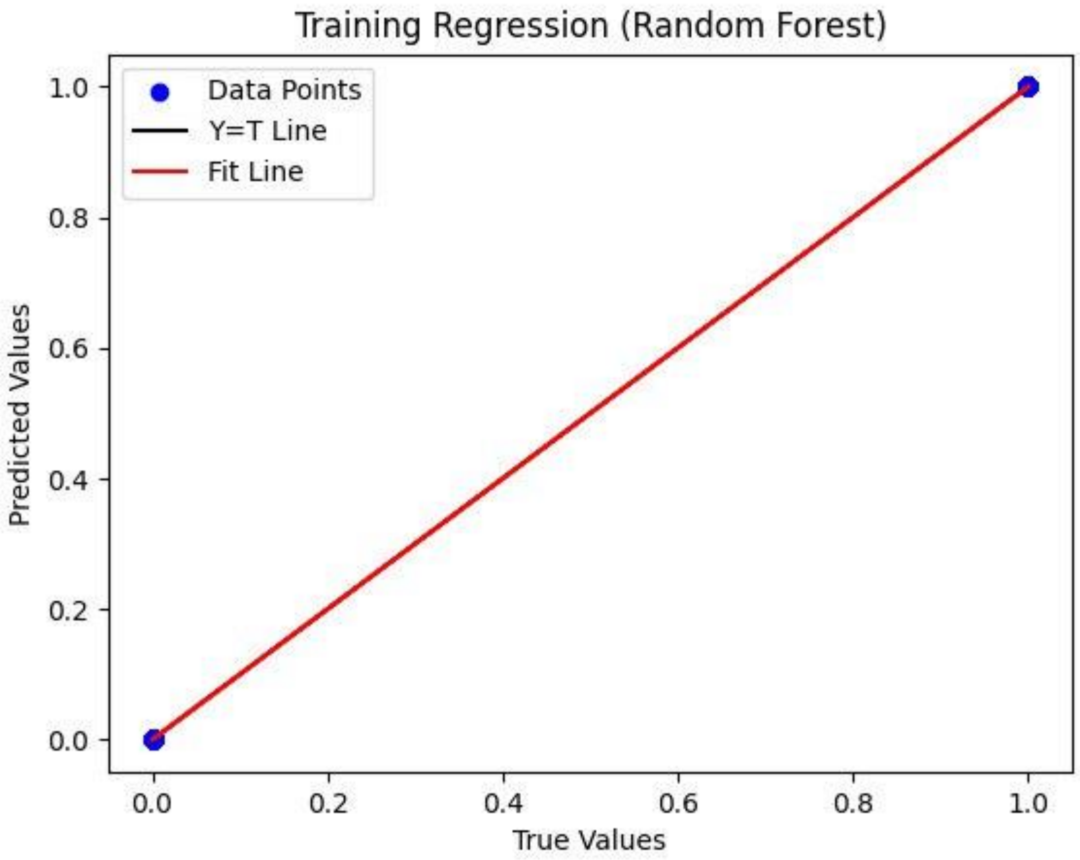

Fig. 34 Training Regression for Random Forest

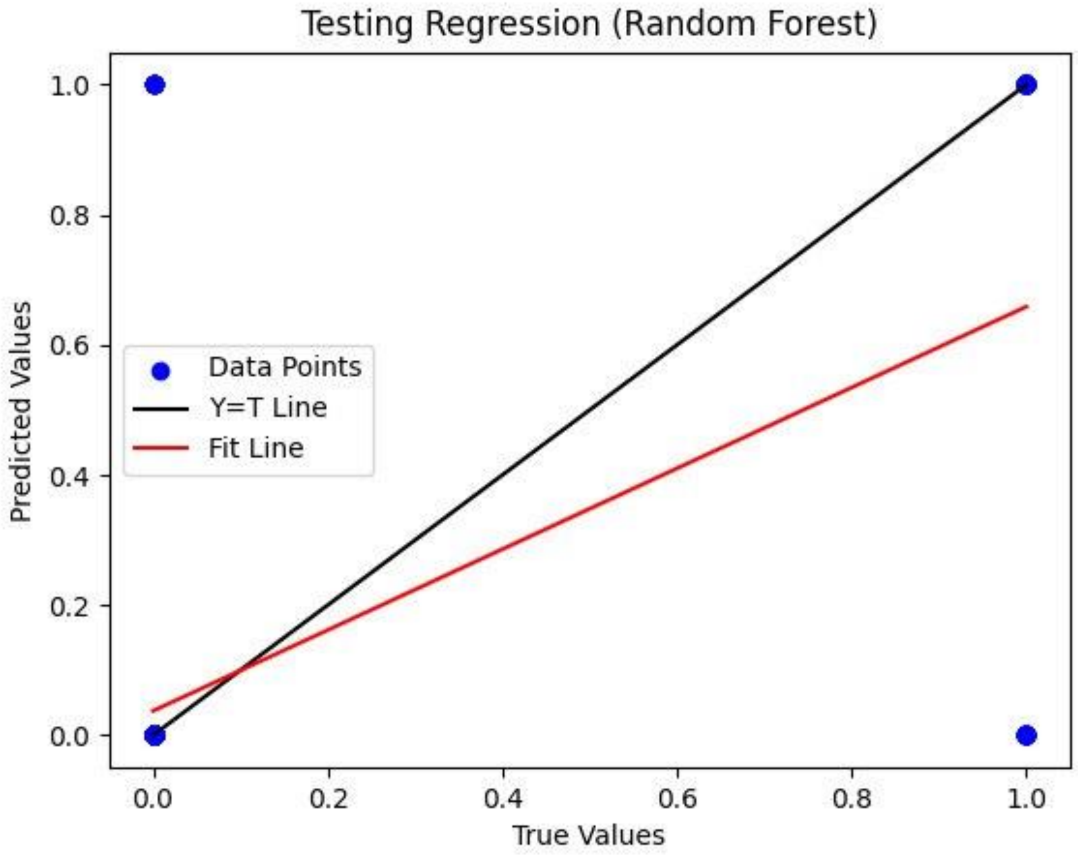

Fig. 35 Testing Regression for Random Forest

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Random Forest: Evaluation Metrics

Metric	Value
Accuracy	0.85
Precision	0.869698574517852
Recall	0.810673490580033
F1 Score	0.827412885310189

Fig. 36 Evaluation Metrics
for Random Forest

Deep Learning

- Neural Networks: Deep learning uses artificial neural networks with multiple layers to mimic the way the human brain processes information.
- High Accuracy: It achieves state-of-the-art accuracy in tasks such as image recognition, natural language processing, and speech recognition due to its ability to learn hierarchical features.
- Data-Driven: Deep learning models thrive on large datasets, as they use vast amounts of data to improve their performance and generalization.
- Wide Applications: Deep learning powers cutting-edge advancements in different fields

Convolution Neural Network

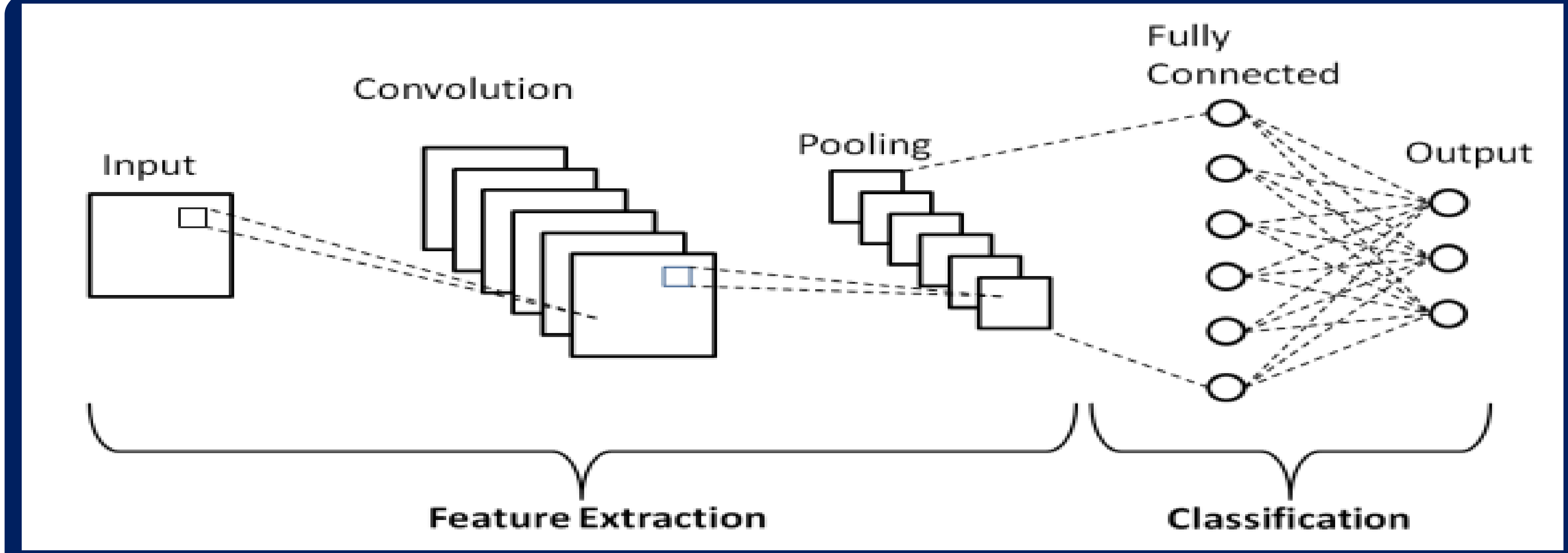

Fig. 37 CNN Architecture [21]

1. Image Processing: CNNs specialize in analyzing image data by recognizing patterns like edges and textures.

2. Feature Extraction: They use convolution layers to automatically learn features, reducing manual effort.

Convolution Neural Network

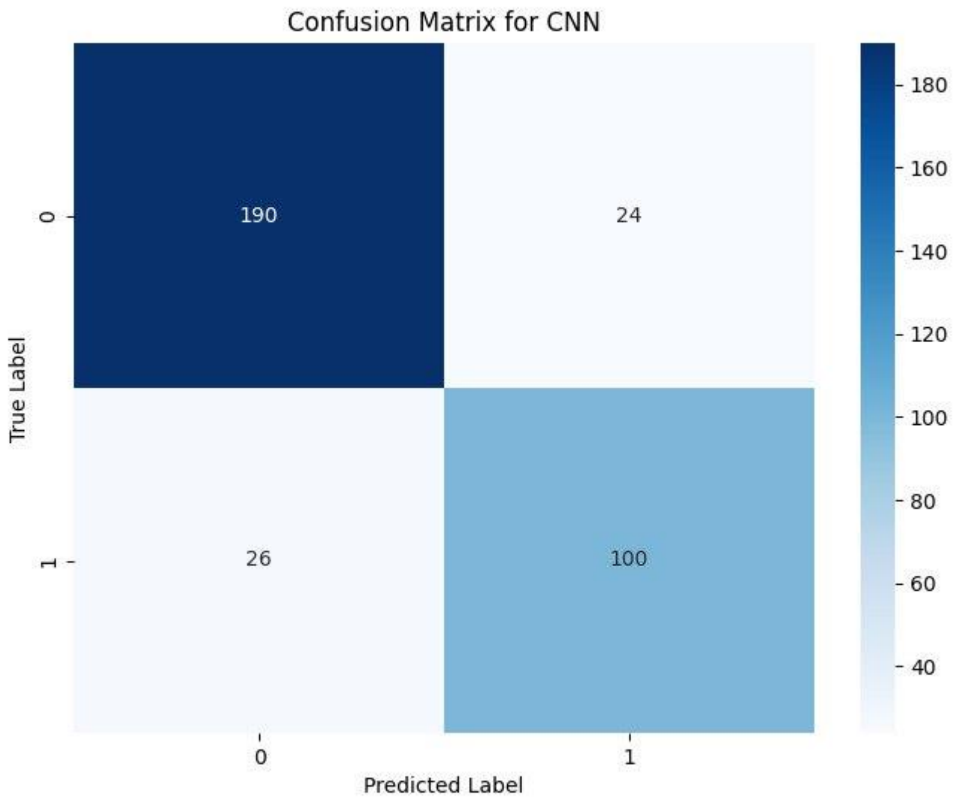

Fig. 38 Confusion Matrix for CNN

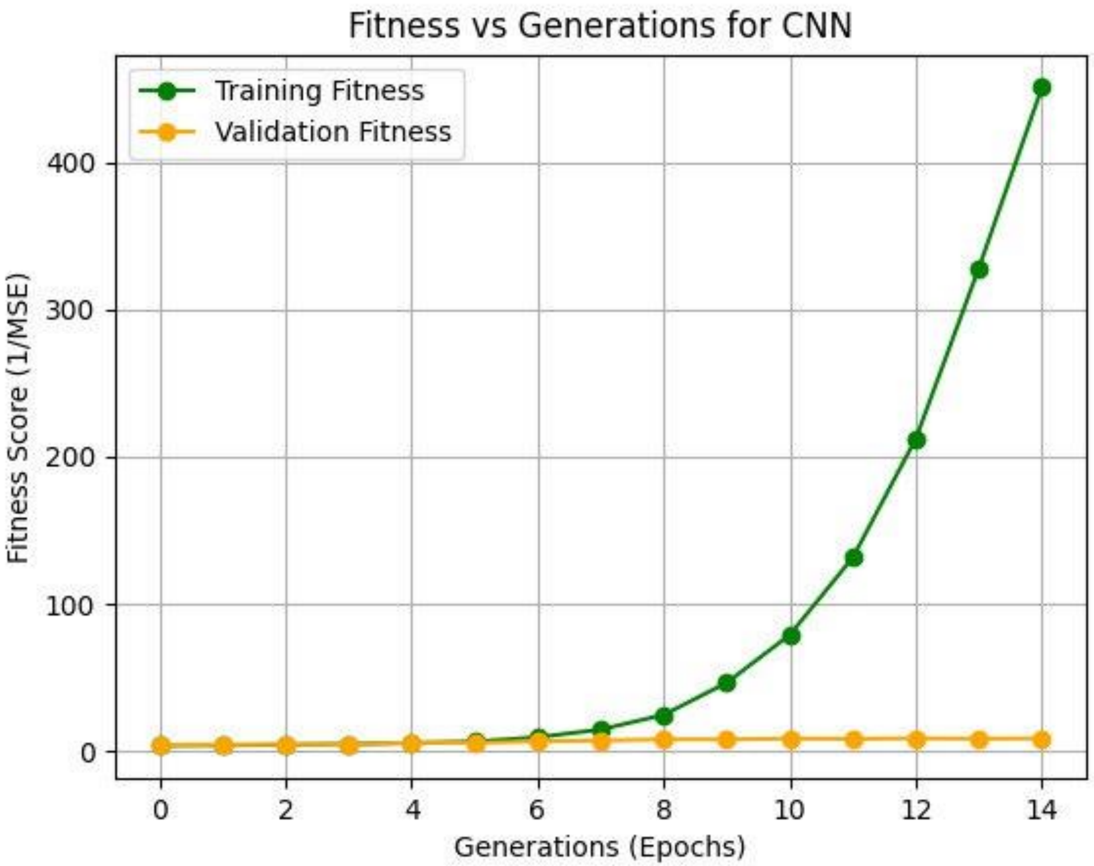

Fig. 39 Fitness vs Generations for CNN

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Convolution Neural Network

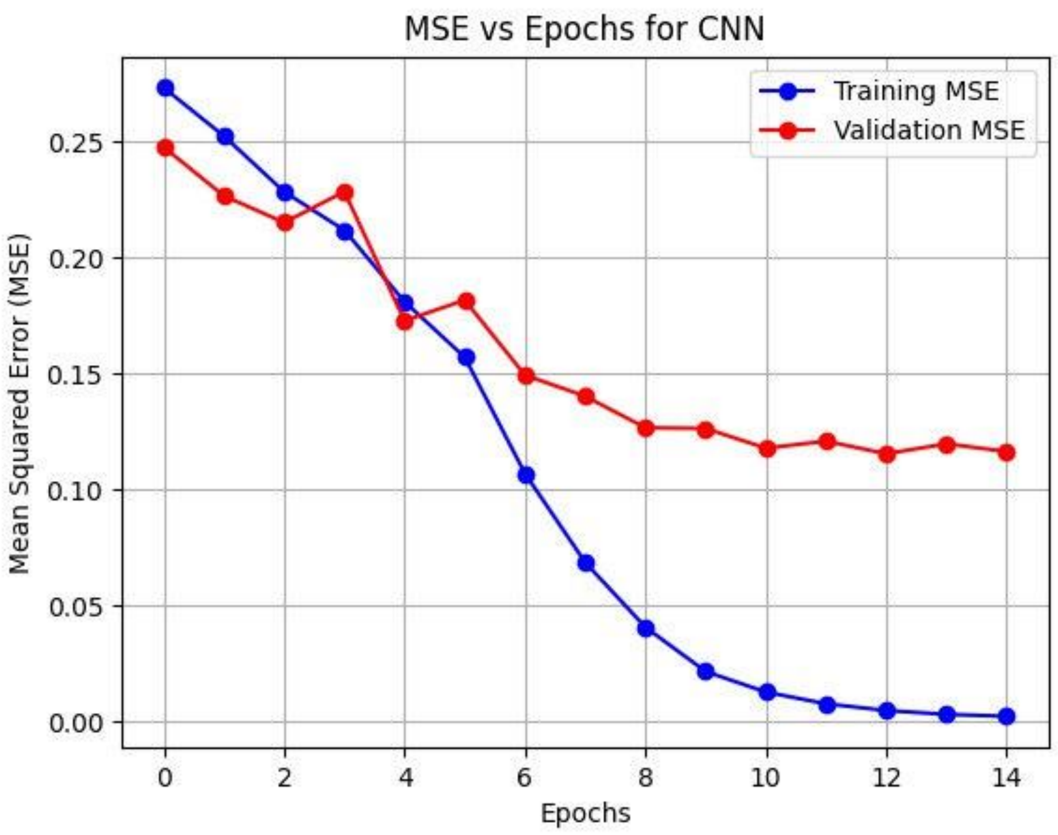

Fig. 40 MSE vs Epochs for CNN

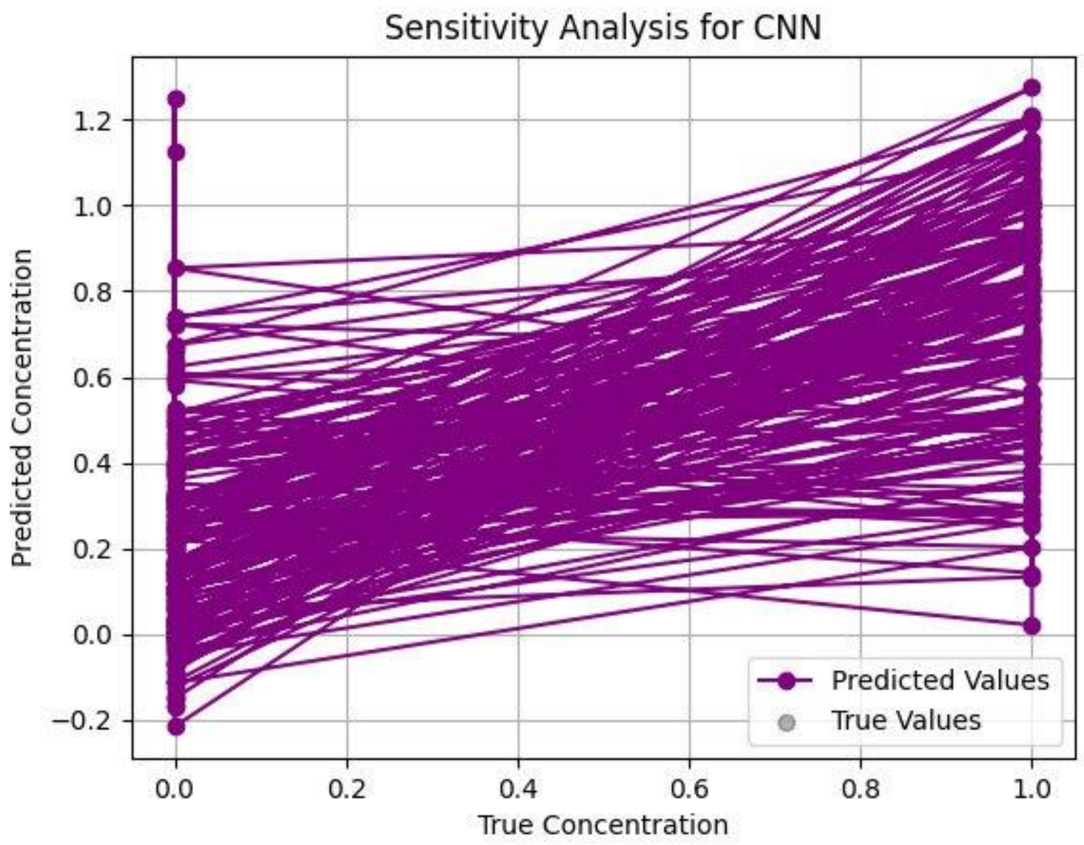

Fig. 41 Sensitivity Analysis for CNN

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Convolution Neural Network

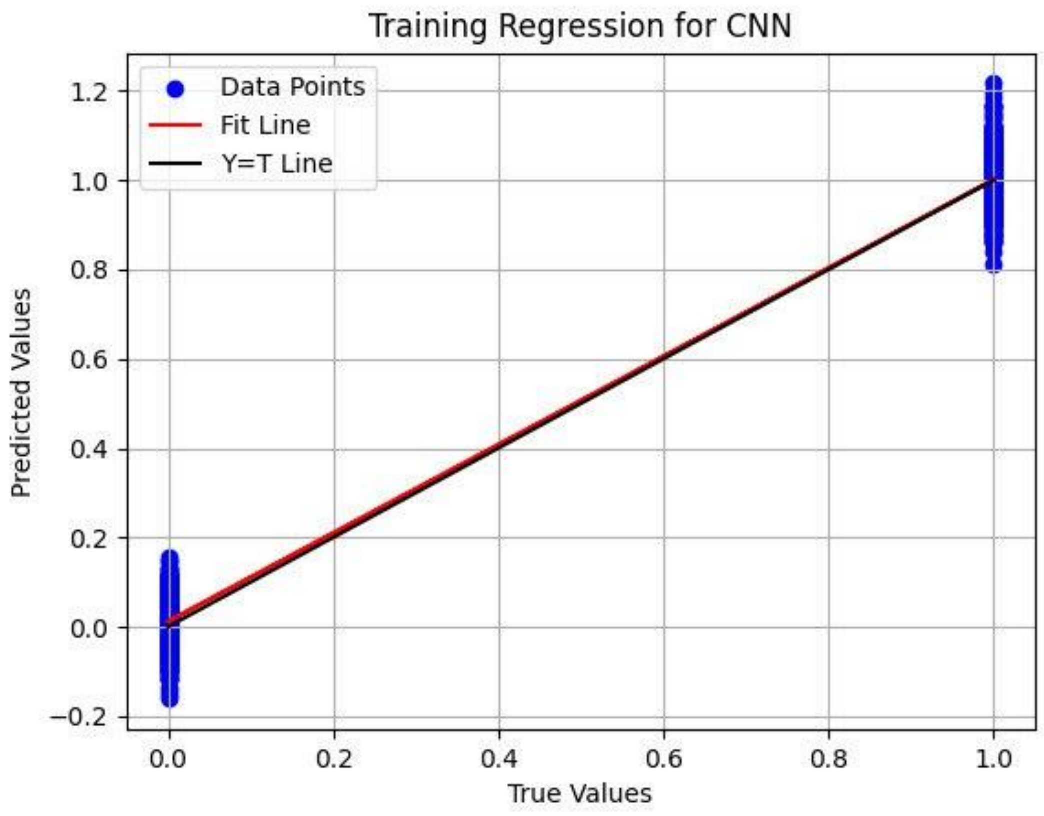

Fig. 42 Training Regression for CNN

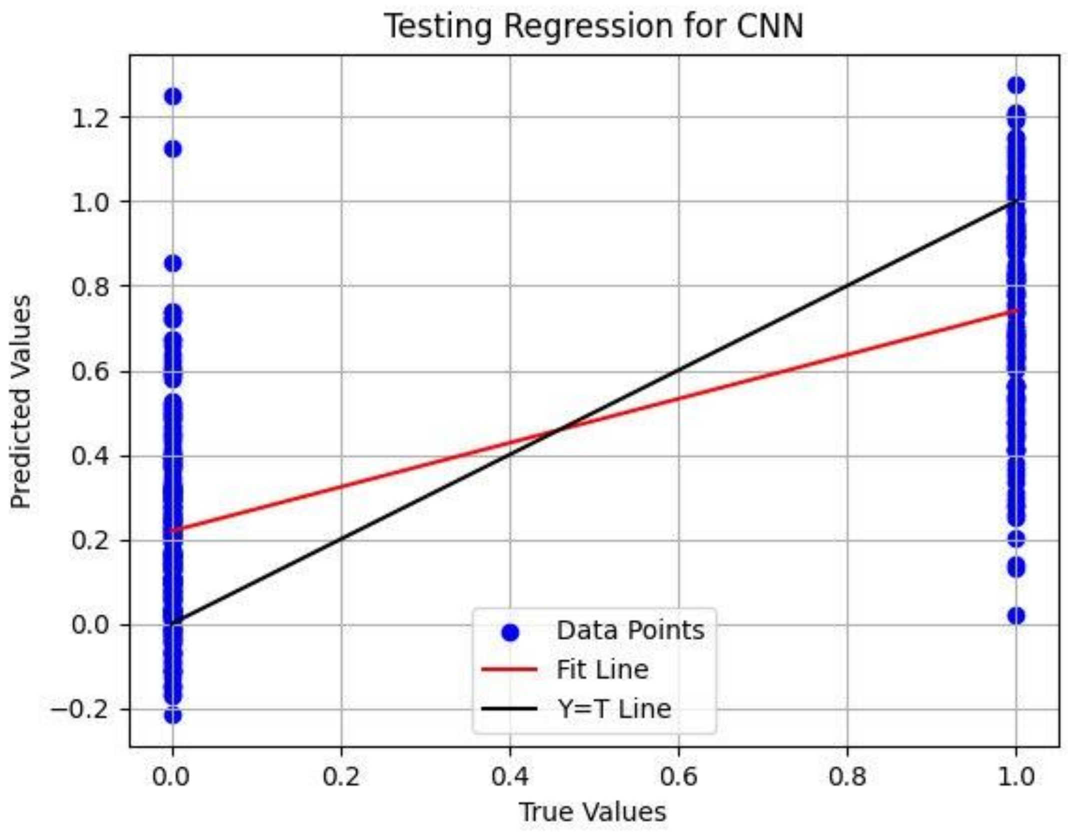

Fig. 43 Testing Regression for CNN

Convolution Neural Network

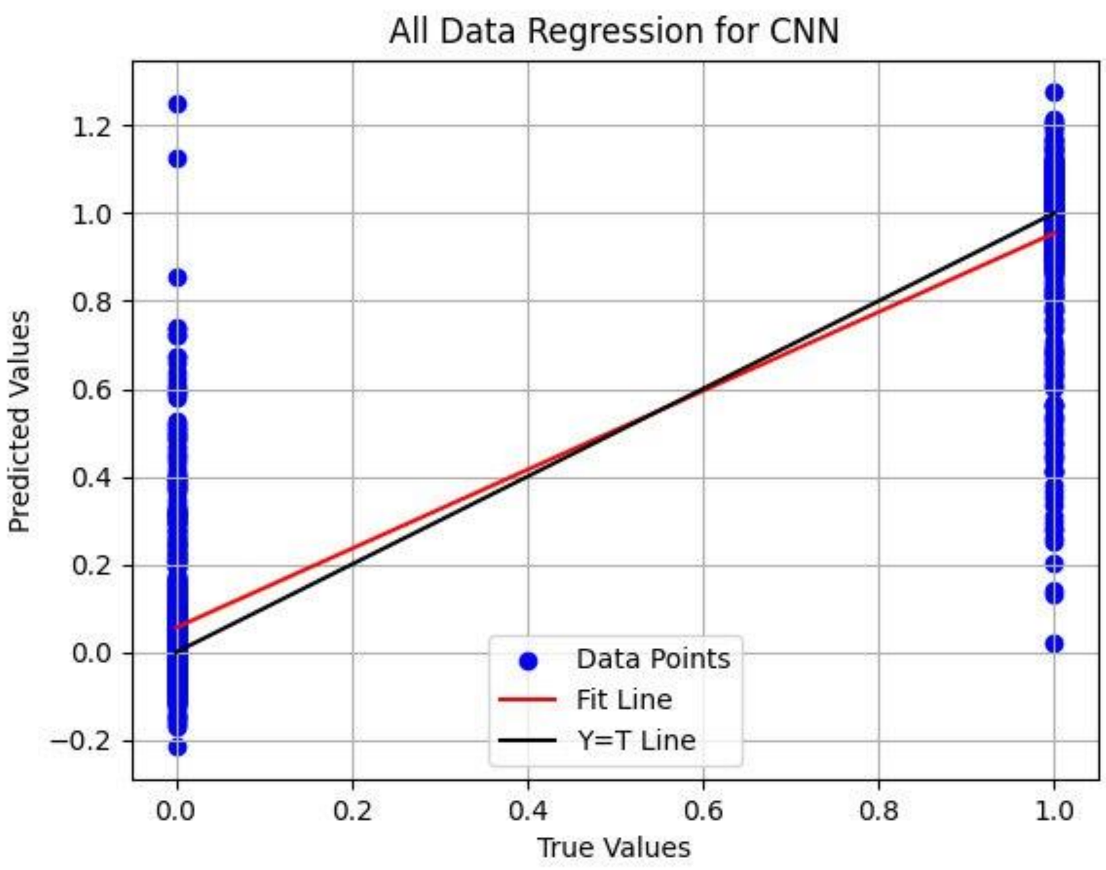

Fig. 44 All Data
Regression for CNN

Convolution Neural Network: Evaluation Metrics

Metric	Score
Accuracy	0.8529411764705882
Precision	0.8525107175486686
Recall	0.8529411764705882
F1 Score	0.8526949384404936

Fig. 45 Evaluation Metrics for CNN

Metric	Train	Test
MSE	0.003122605769182416	0.11548038971582837
R2 Score	0.9871985316276551	0.5049127340316771

Fig. 46 Model Metrics for CNN

Region Based CNN

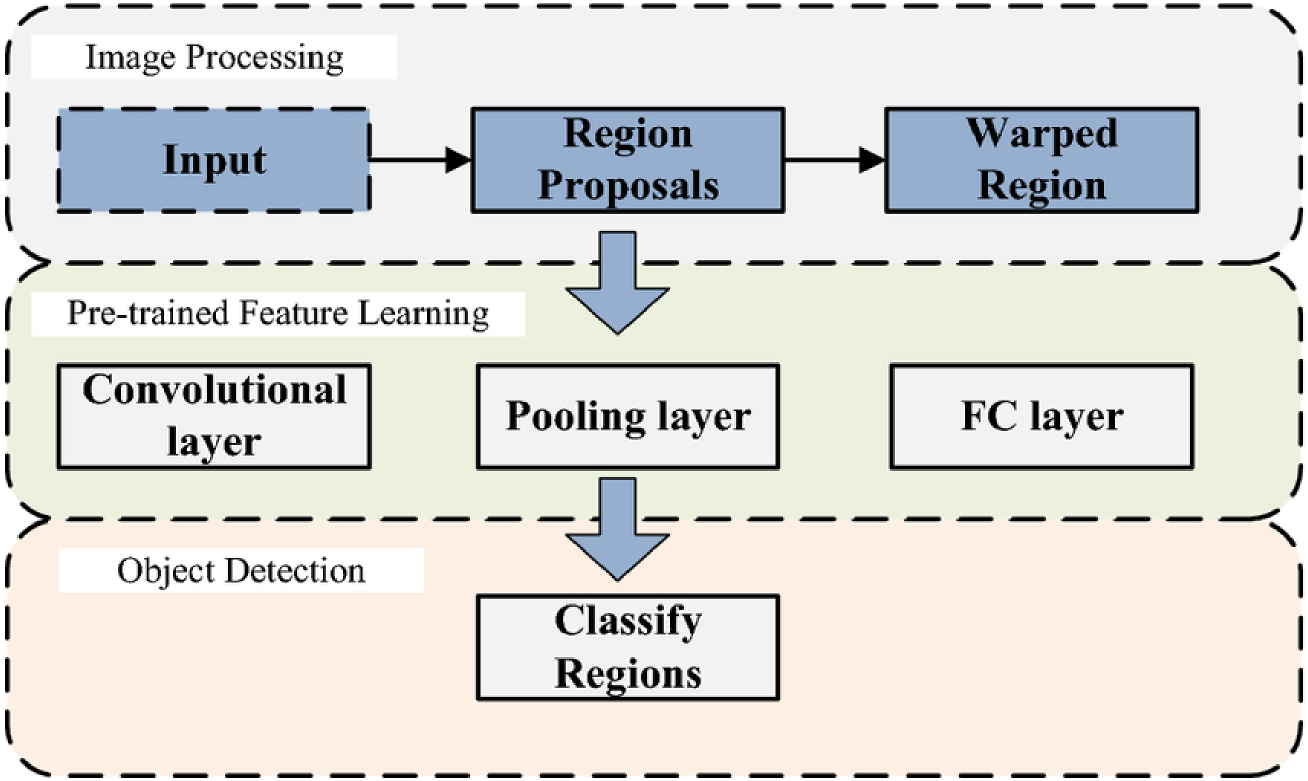

Fig. 47 RCNN Architecture [22]

1. Object Detection: RCNN is designed for detecting objects in images.
2. Region Proposals: It generates region proposals before classification.
3. Accurate: Improves accuracy compared to traditional methods.
4. Requires more computation due to its multi-stage process.

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Region Based CNN

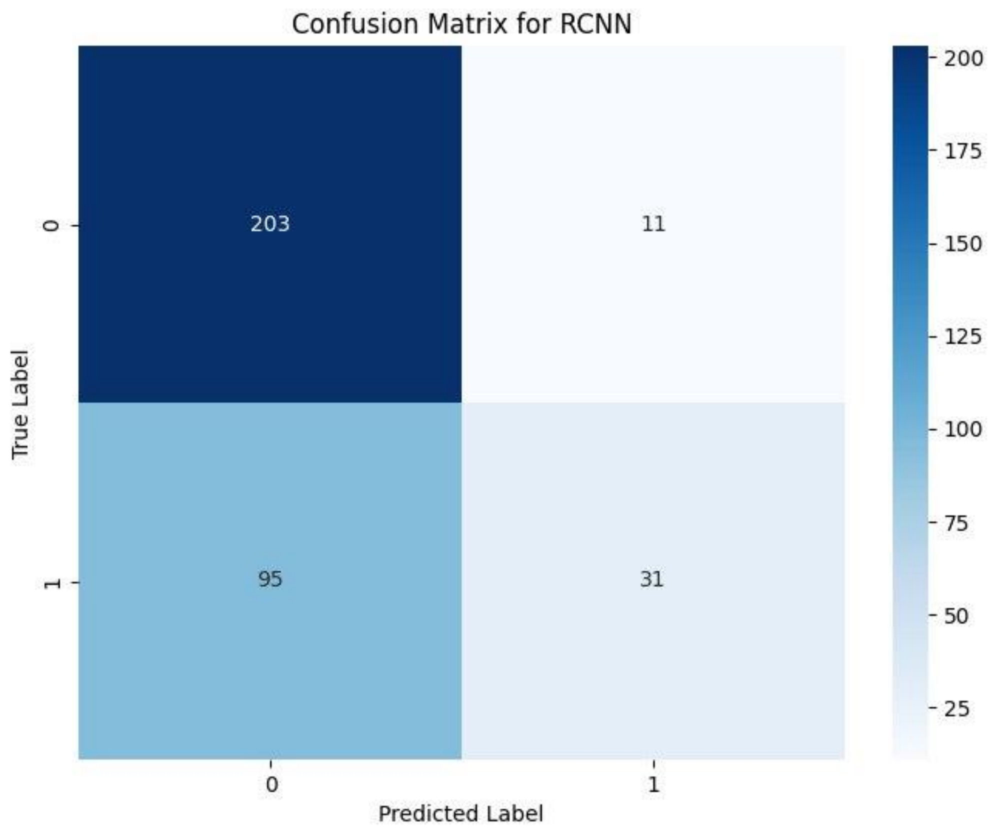

Fig. 48 Confusion Matrix for RCNN

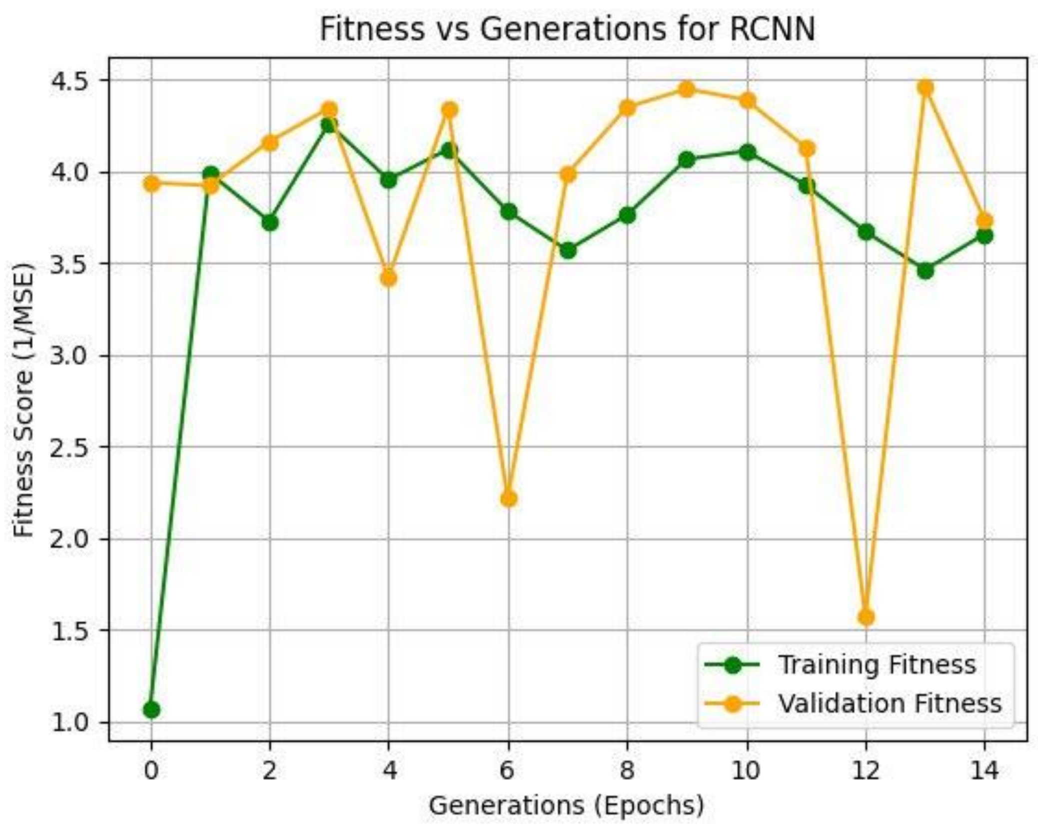

Fig. 49 Fitness vs Generations for RCNN

Region Based CNN

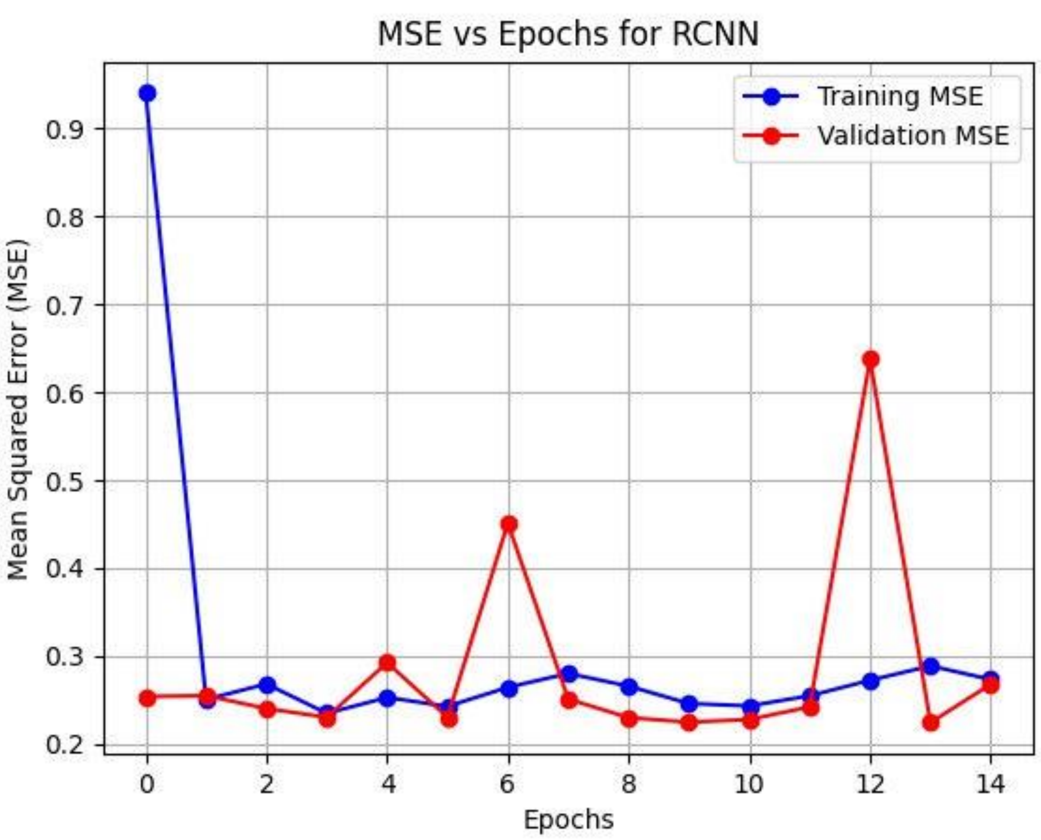

Fig. 50 MSE vs Epochs for RCNN

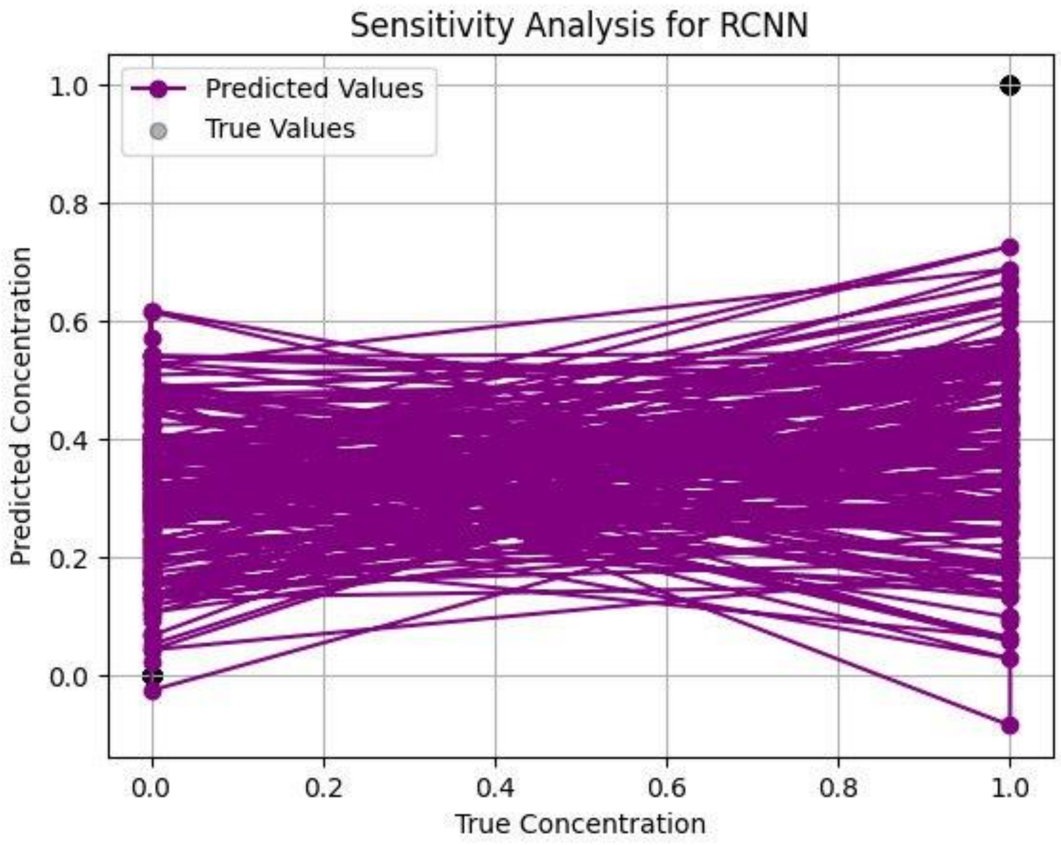

Fig. 51 Sensitivity Analysis for RCNN

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Region Based CNN

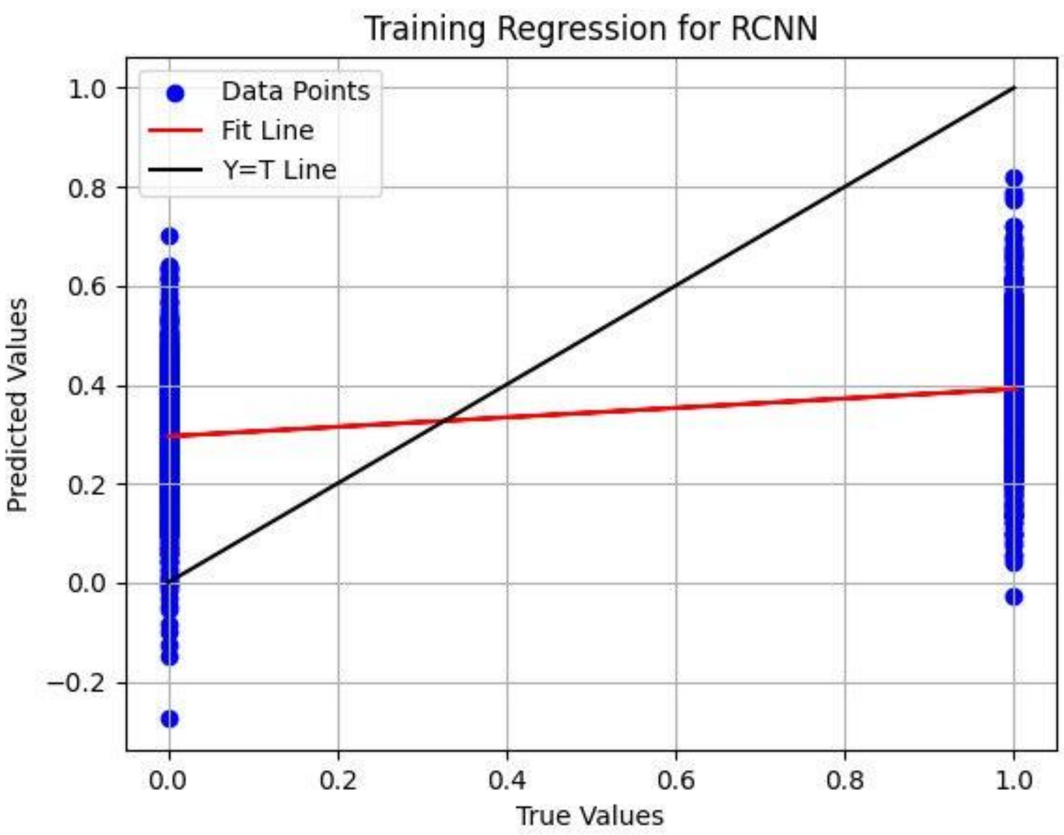

Fig. 52 Training Regression for RCNN

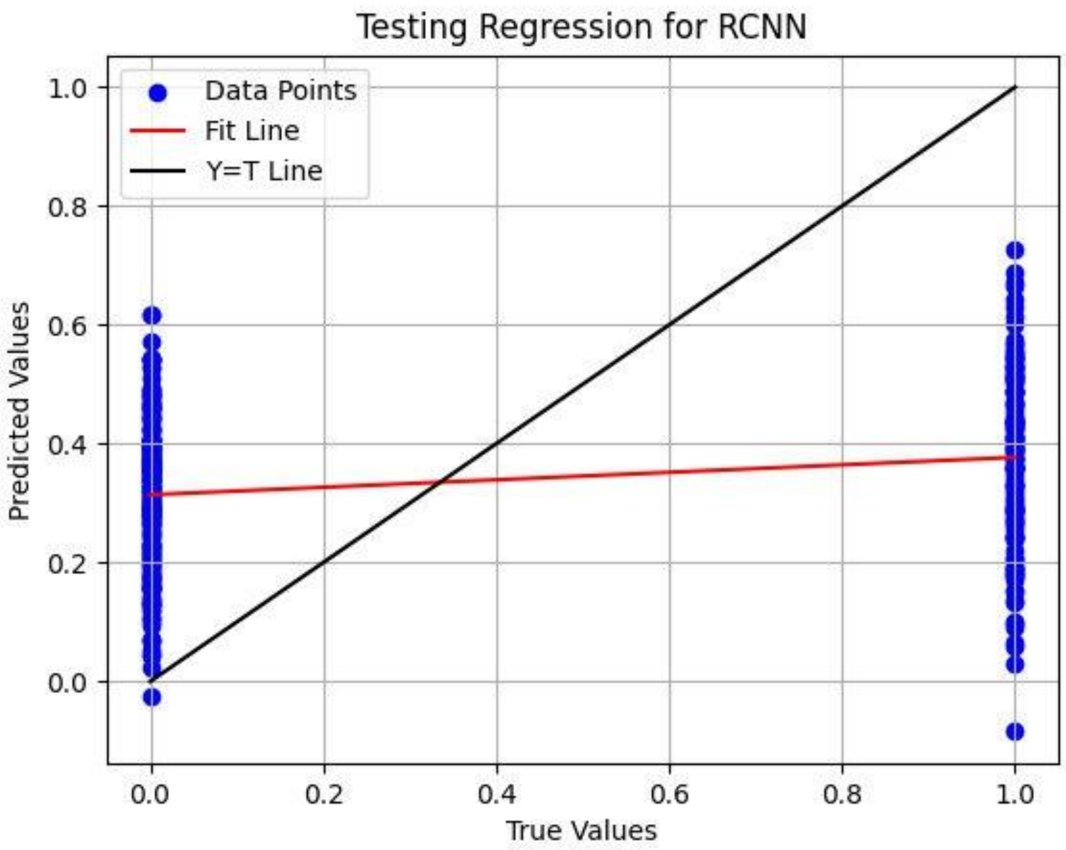

Fig. 53 Testing Regression for RCNN

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Region Based CNN

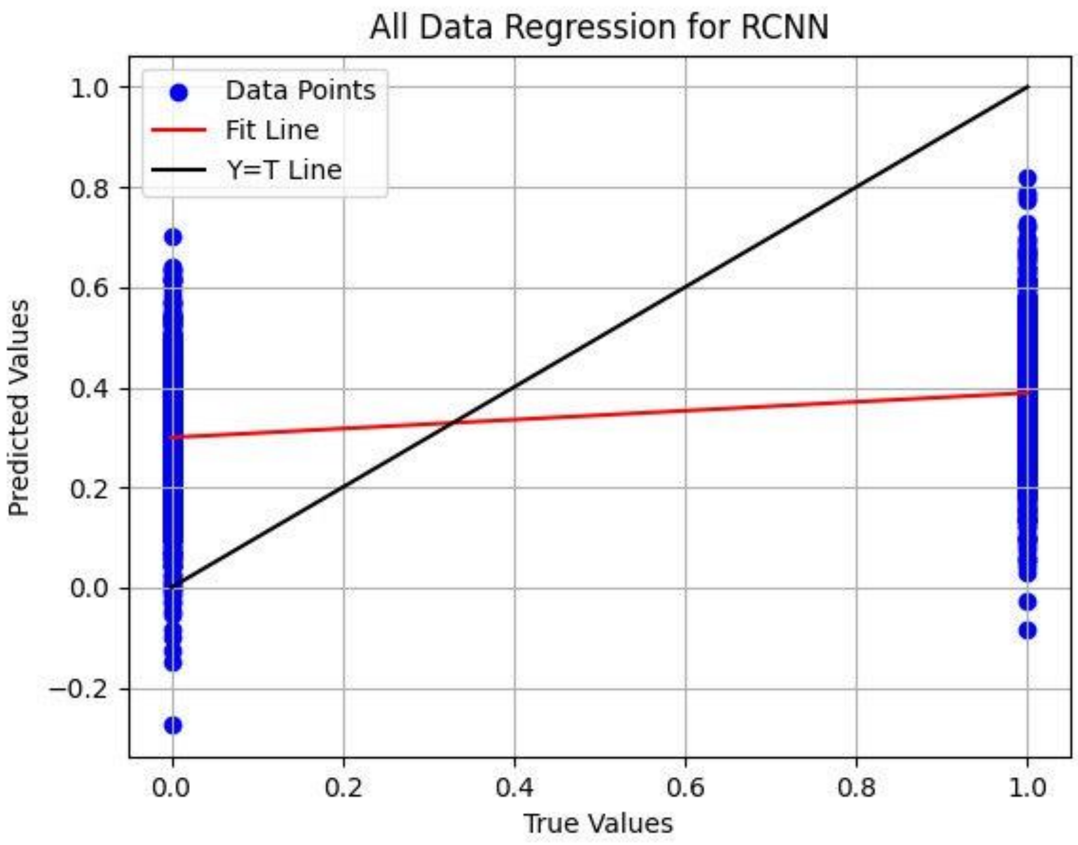

Fig. 54 All Data Regression for RCNN

Region Based CNN: Evaluation Metrics

Metric	Score
Accuracy	0.688235294117647
Precision	0.702289774970391
Recall	0.688235294117647
F1 Score	0.635868566176471

Fig. 55 Evaluation Metrics for RCNN

Metric	Train	Test
MSE	0.225199130097909	0.224222622192482
R2 Score	0.0767694711685181	0.0387131571769714

Fig. 56 Model Metrics for RCNN

MobileNet

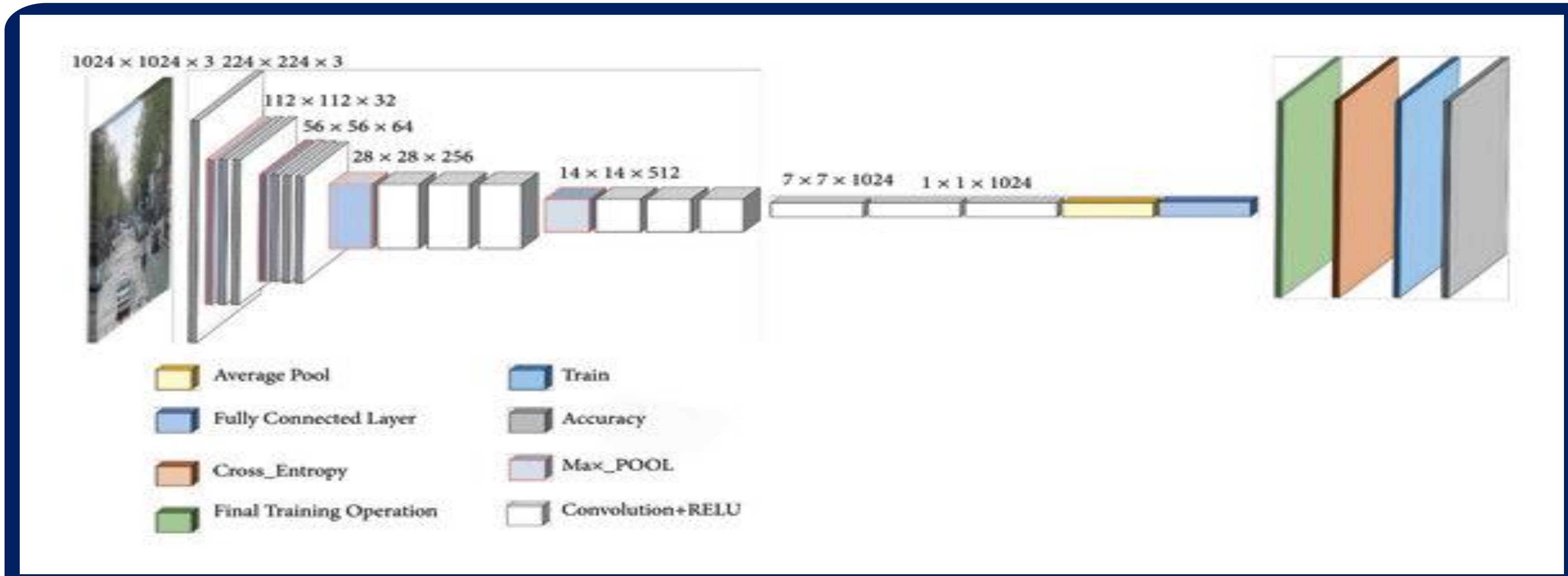

Fig. 57 MobileNet Architecture [23]

1. Lightweight: MobileNet is designed for mobile and embedded devices with limited resources.
2. Real-time Performance: Optimized for fast processing and real-time applications as used in kidney stone detection.

MobileNet

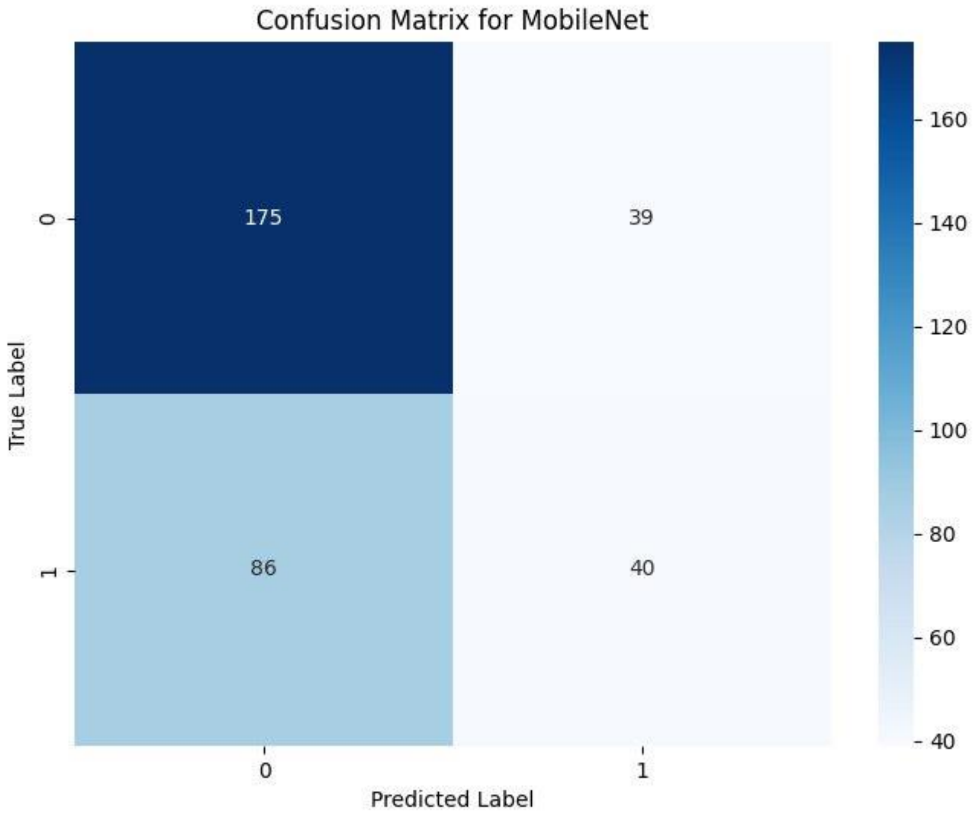

Fig. 58 Confusion Matrix for MobileNet

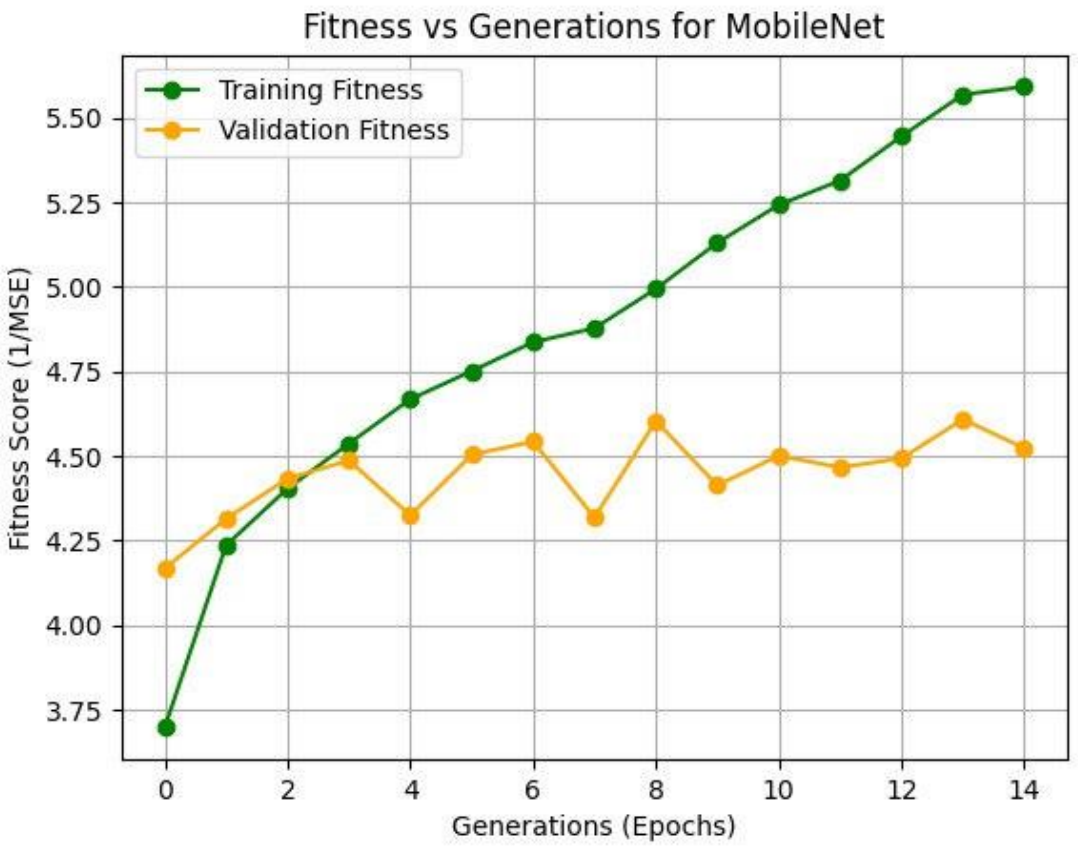

Fig. 59 Fitness vs Generations for MobileNet

MobileNet

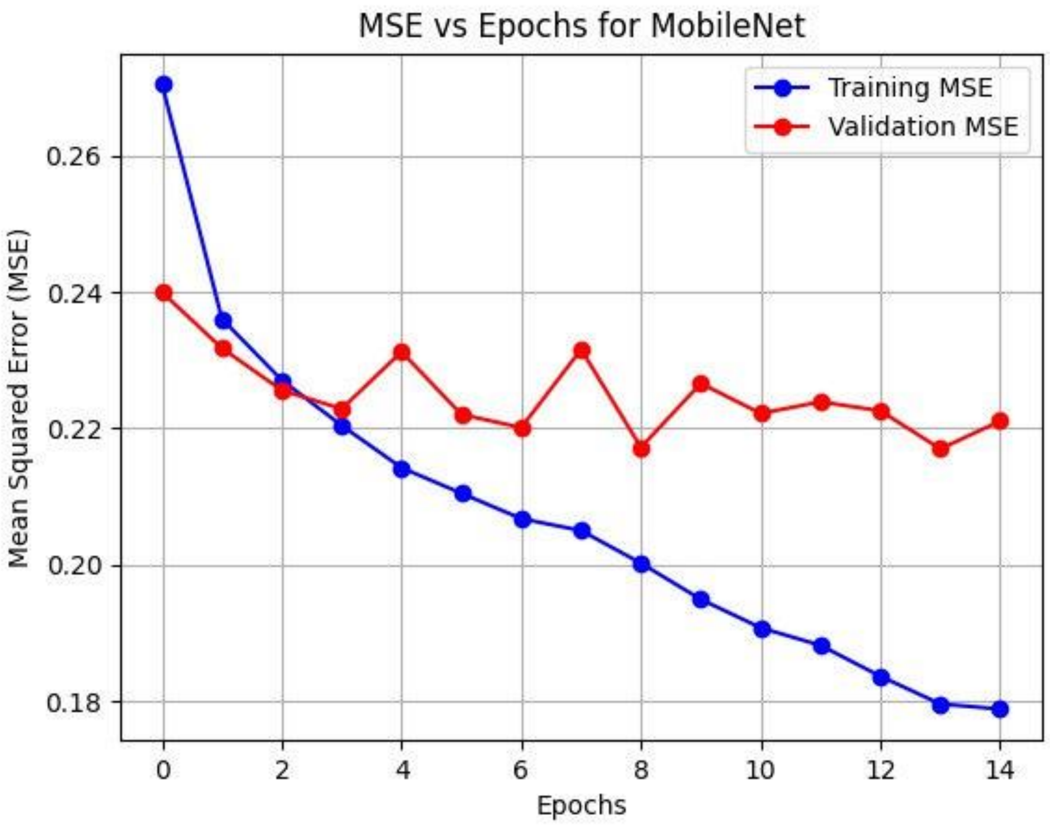

Fig. 60 MSE vs Epochs for MobileNet

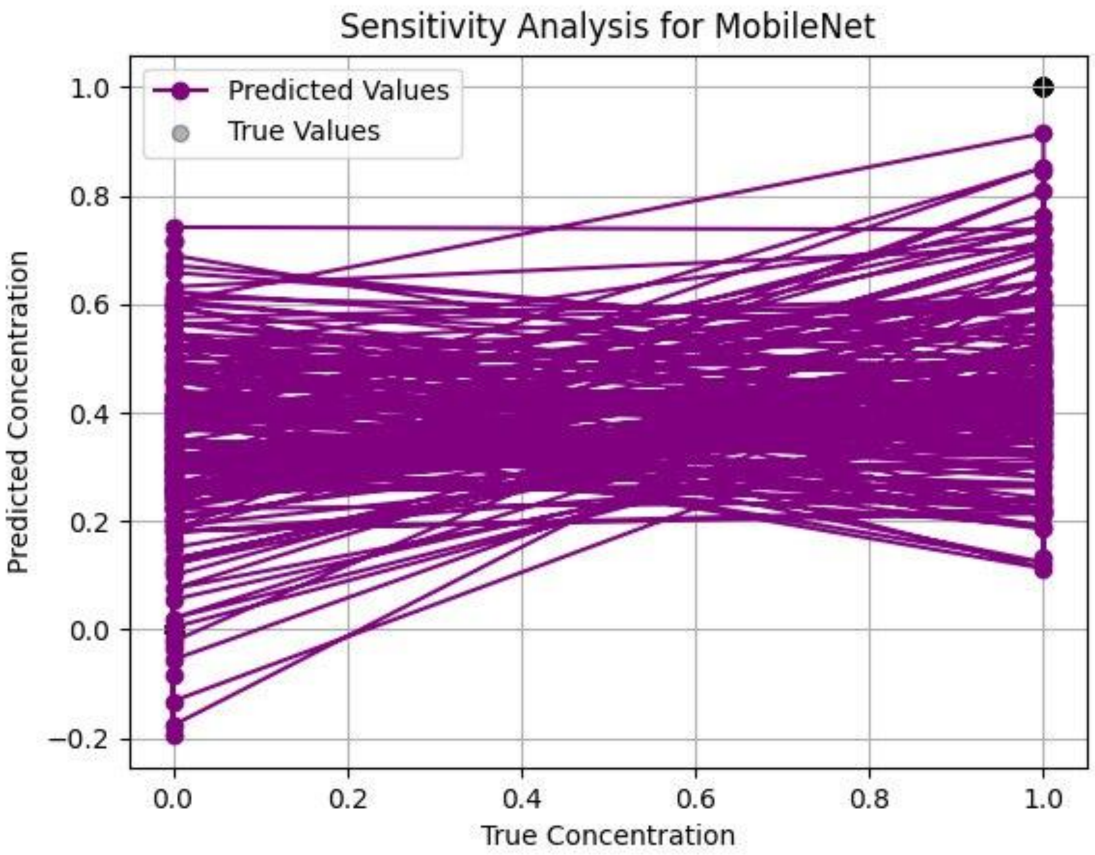

Fig. 61 Sensitivity Analysis for MobileNet

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MobileNet

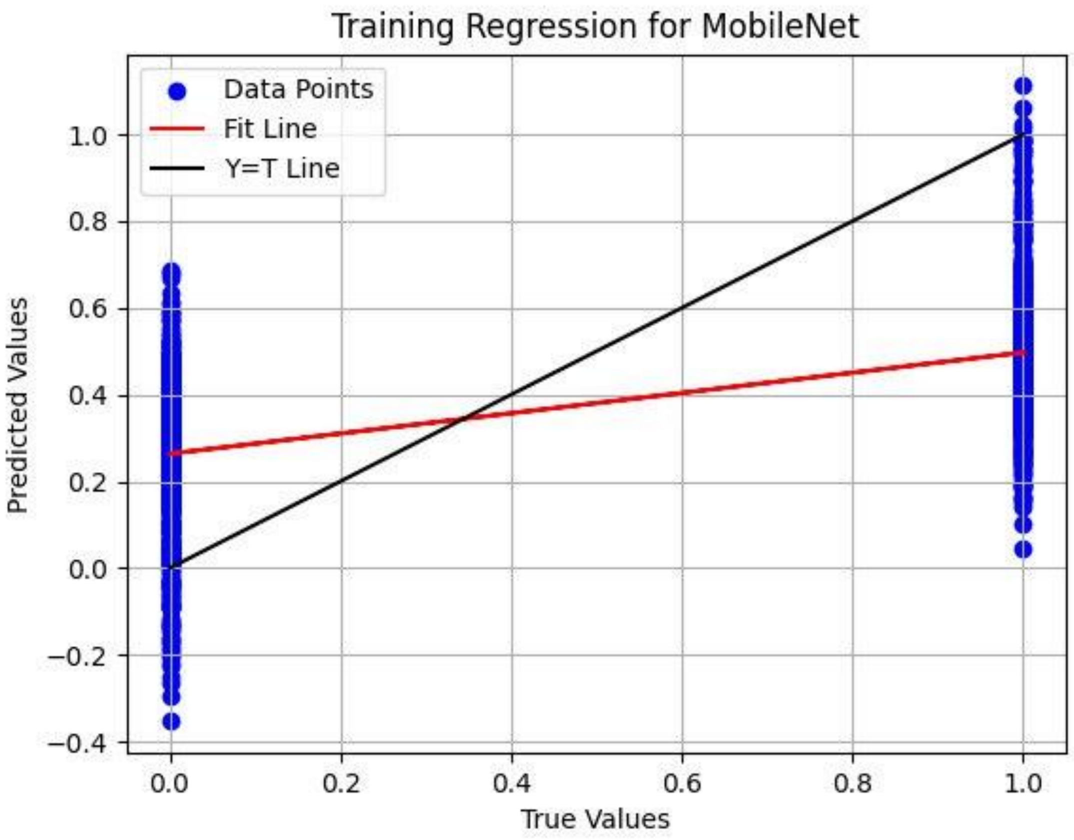

Fig. 62 Training Regression for MobileNet

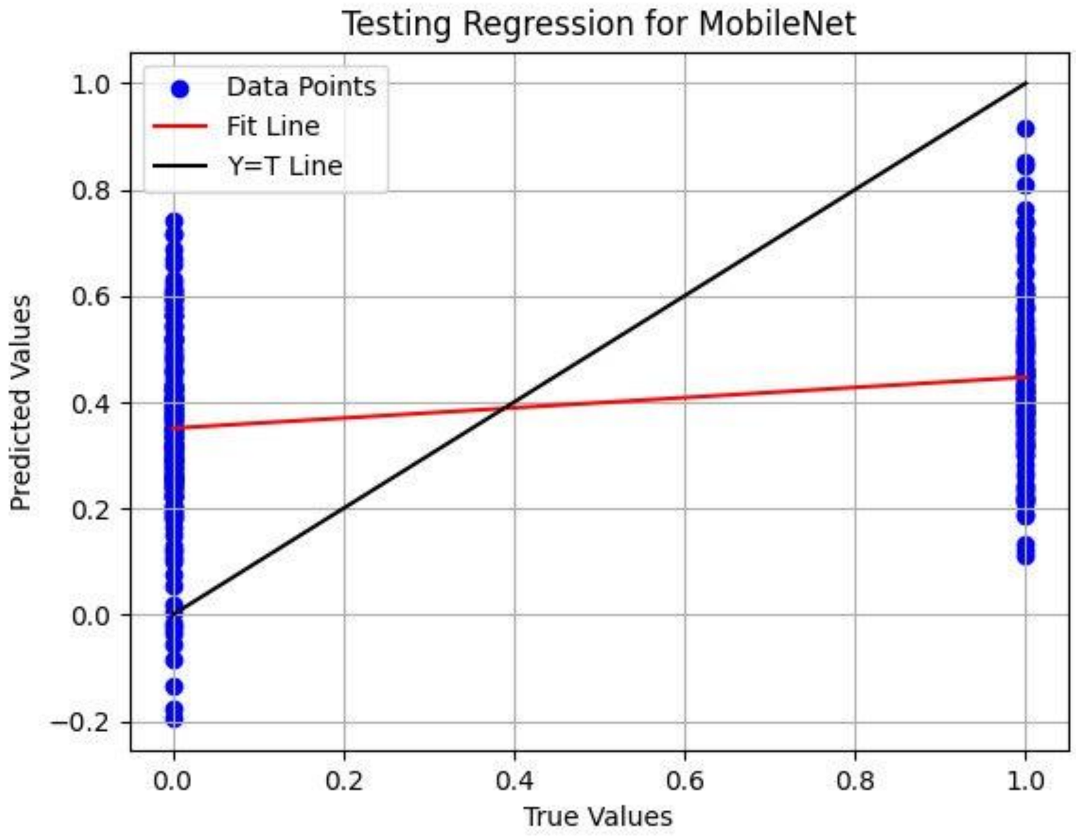

Fig. 63 Testing Regression for MobileNet

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MobileNet

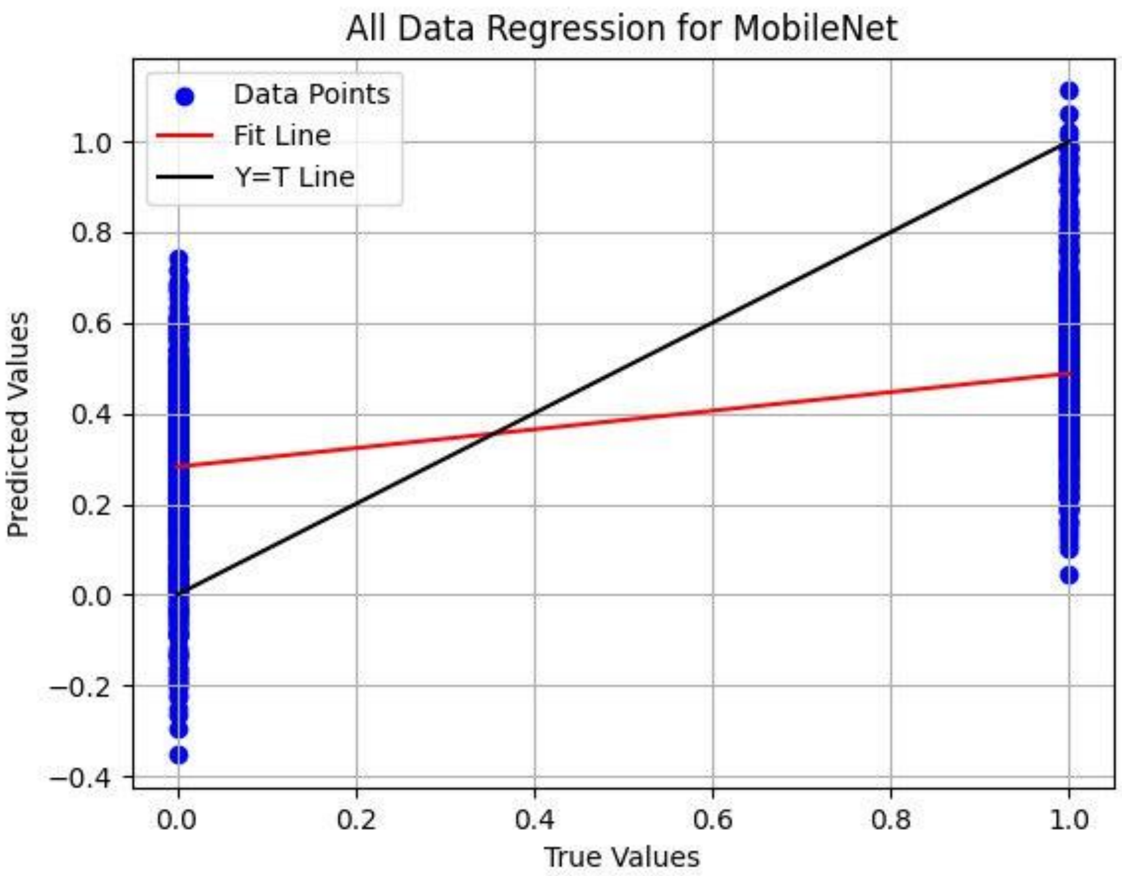

Fig. 64 All Data
Regression for MobileNet

MobileNet: Evaluation Metrics

Metric	Score
Accuracy	0.632352941176471
Precision	0.609658995272778
Recall	0.632352941176471
F1 Score	0.60839688892245

Fig. 65 Evaluation Metrics for MobileNet

Metric	Train	Test
MSE	0.176252538004267	0.216999596678661
R2 Score	0.277431905269623	0.0696797966957092

Fig. 66 Model Metrics for MobileNet

VGG19

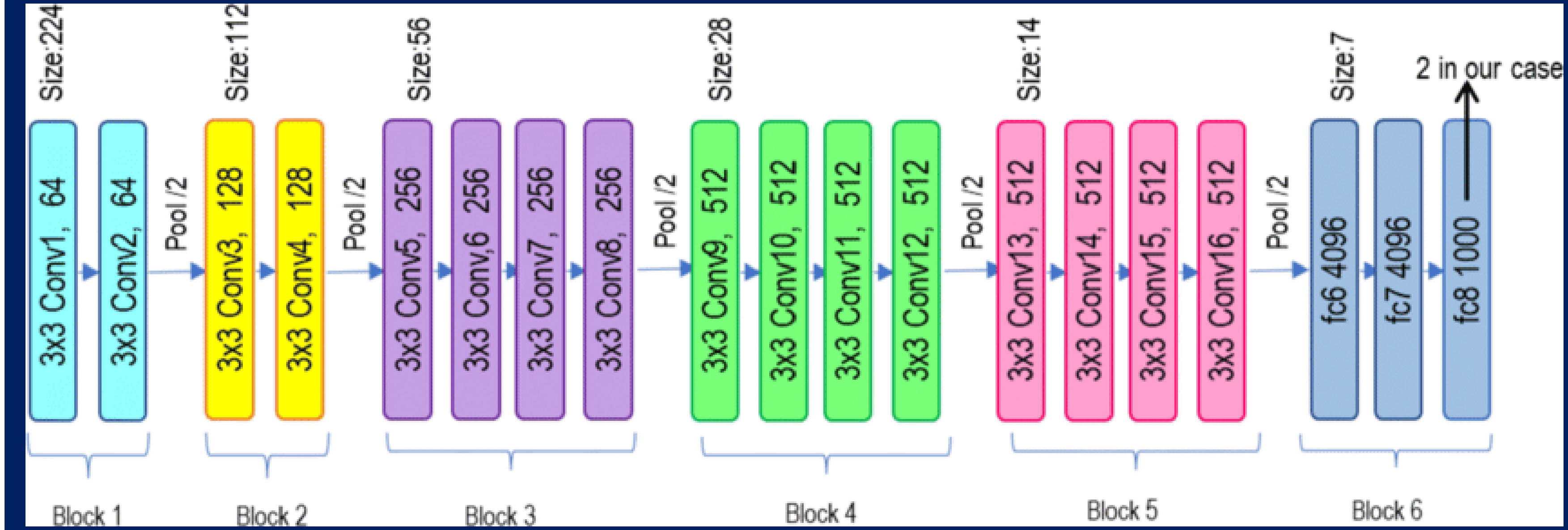

Fig. 67 VGG19 Architecture [24]

1. Deep Architecture: VGG19 has 19 layers, offering a deep network for complex feature extraction.

2. Simple Design: Uses 3x3 convolution filters and 2x2 max-pooling layers, ensuring simplicity and efficiency.

VGG19

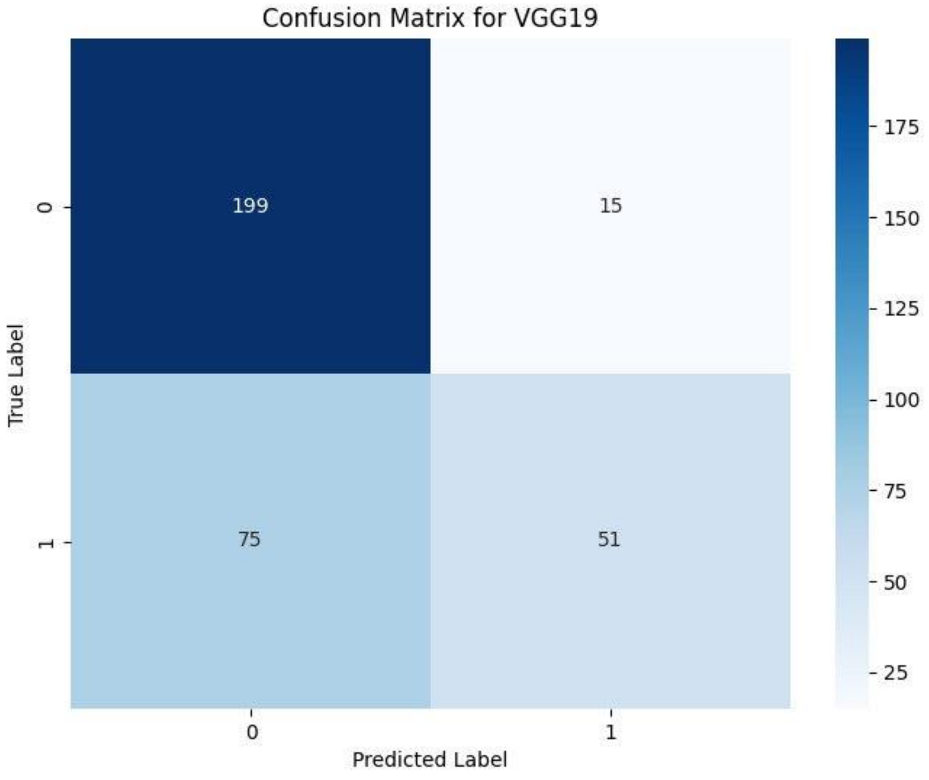

Fig. 68 Confusion Matrix for VGG19

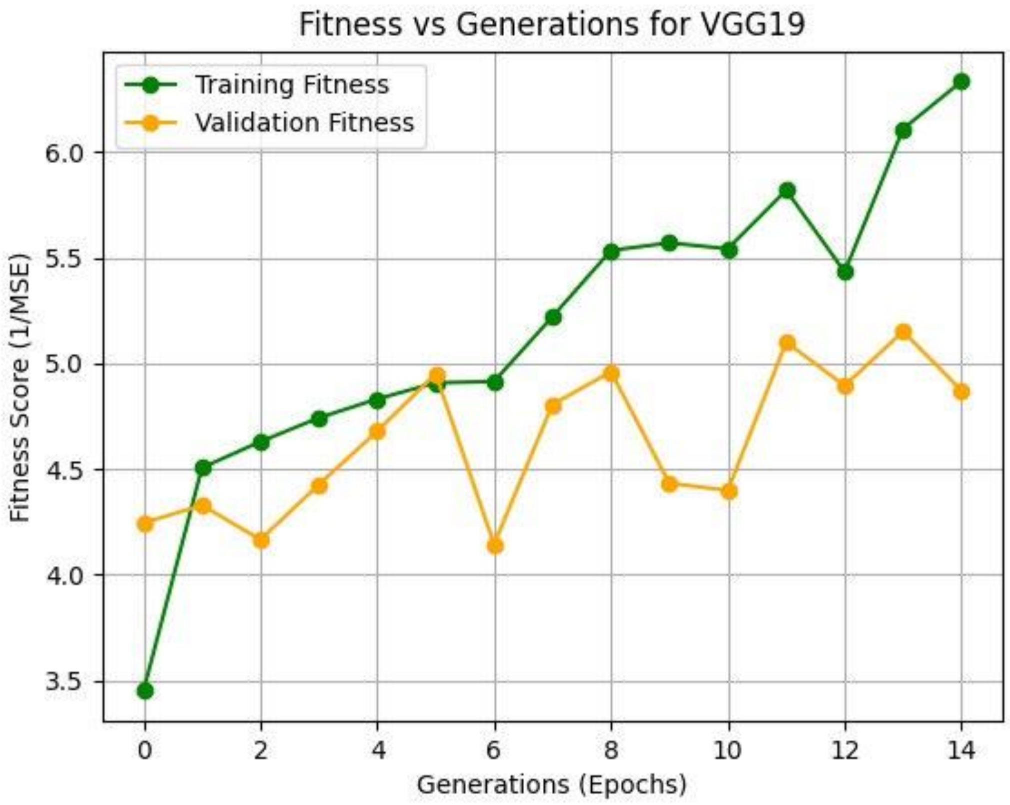

Fig. 69 Fitness vs Generations for VGG19

VGG19

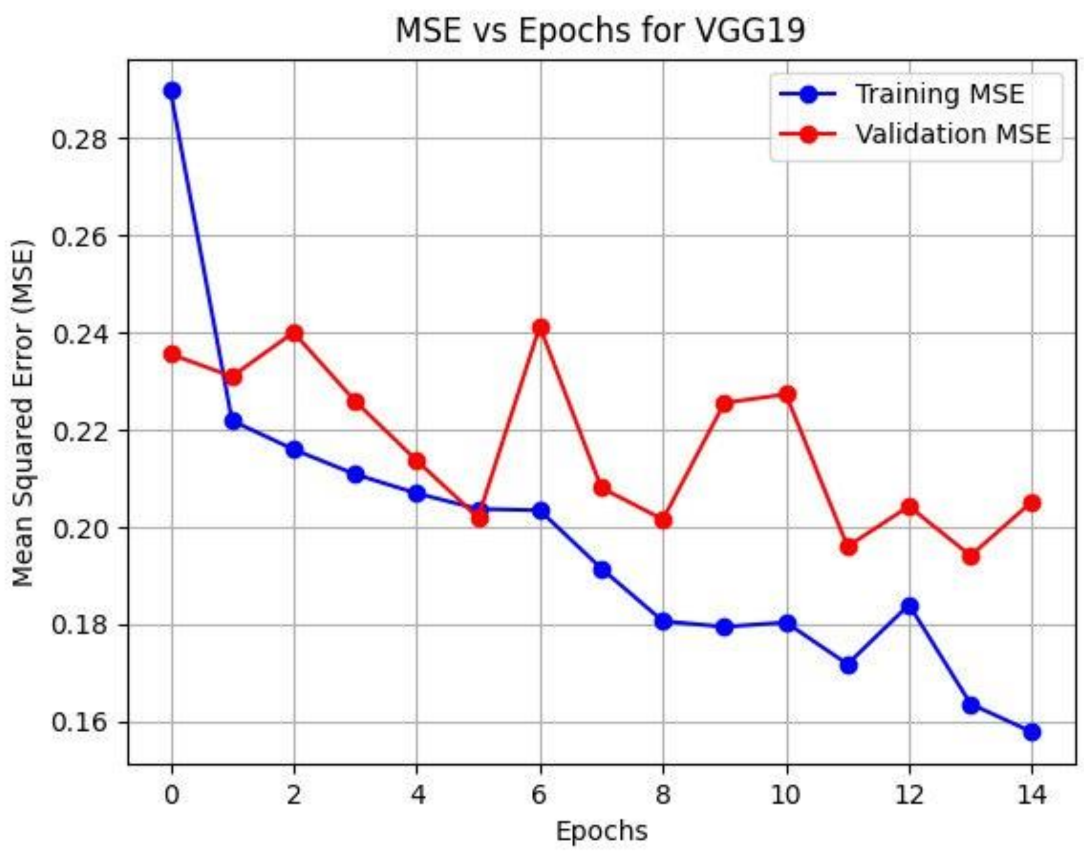

Fig. 70 MSE vs Epochs for VGG19

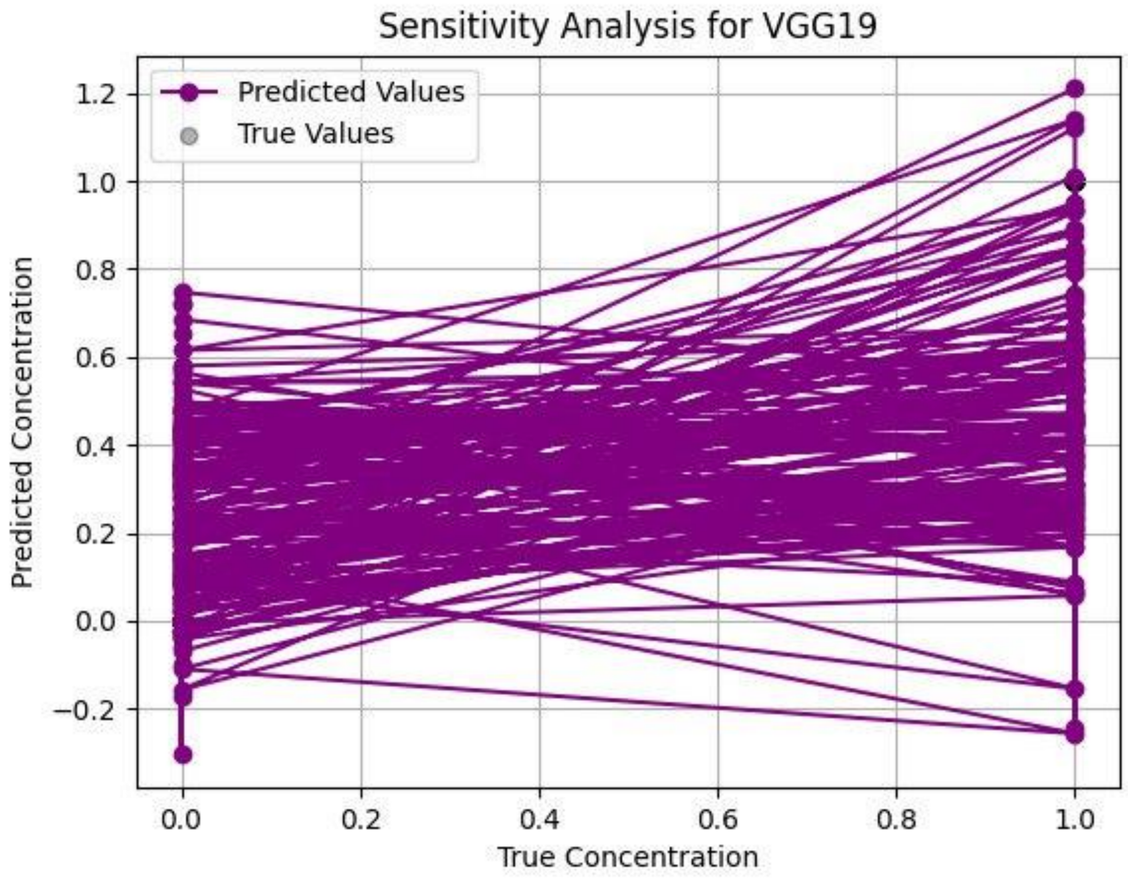

Fig. 71 Sensitivity Analysis for VGG19

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VGG19

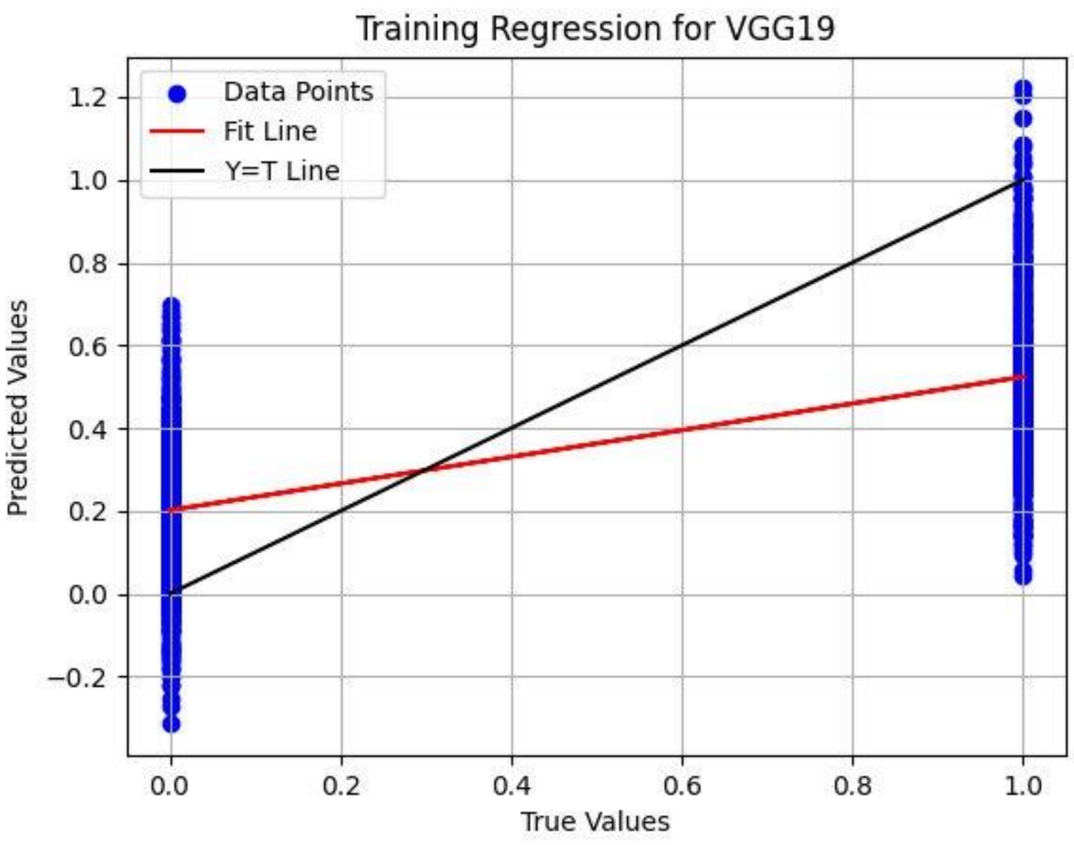

Fig. 72 Training Regression for VGG19

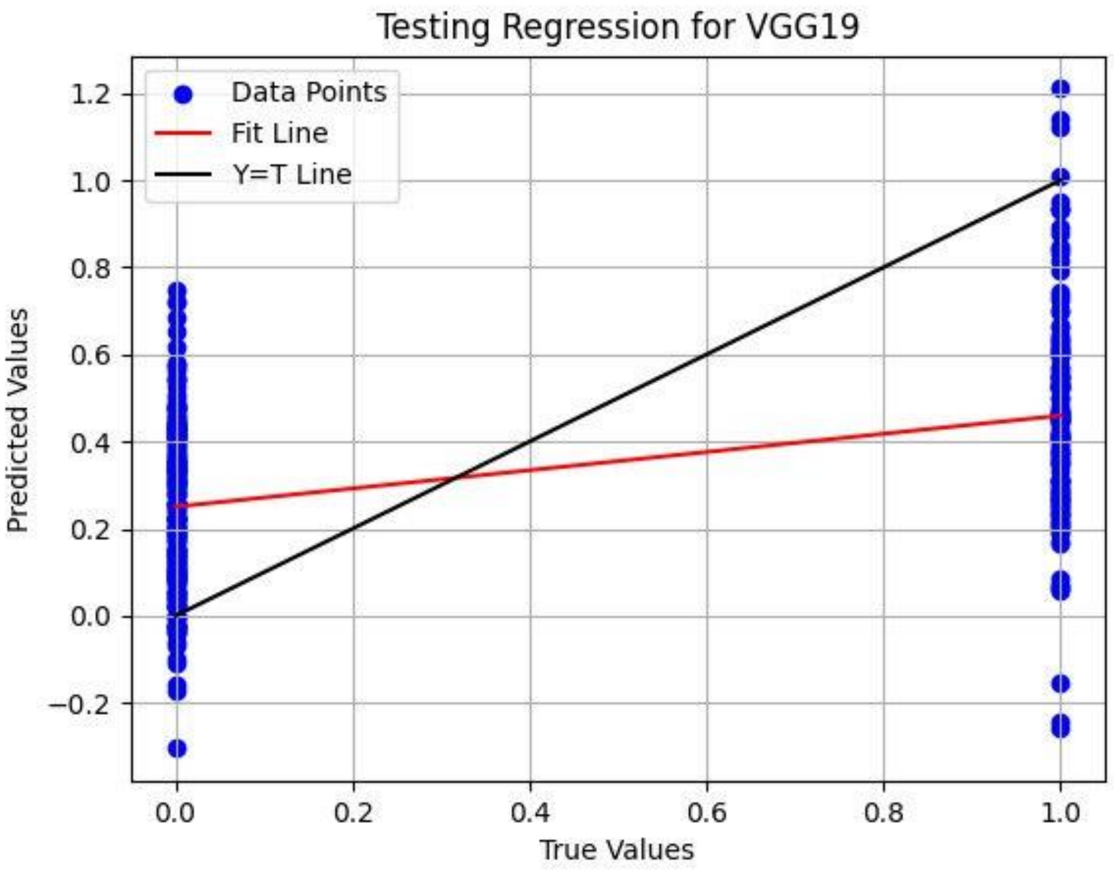

Fig. 73 Testing Regression for VGG19

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VGG19

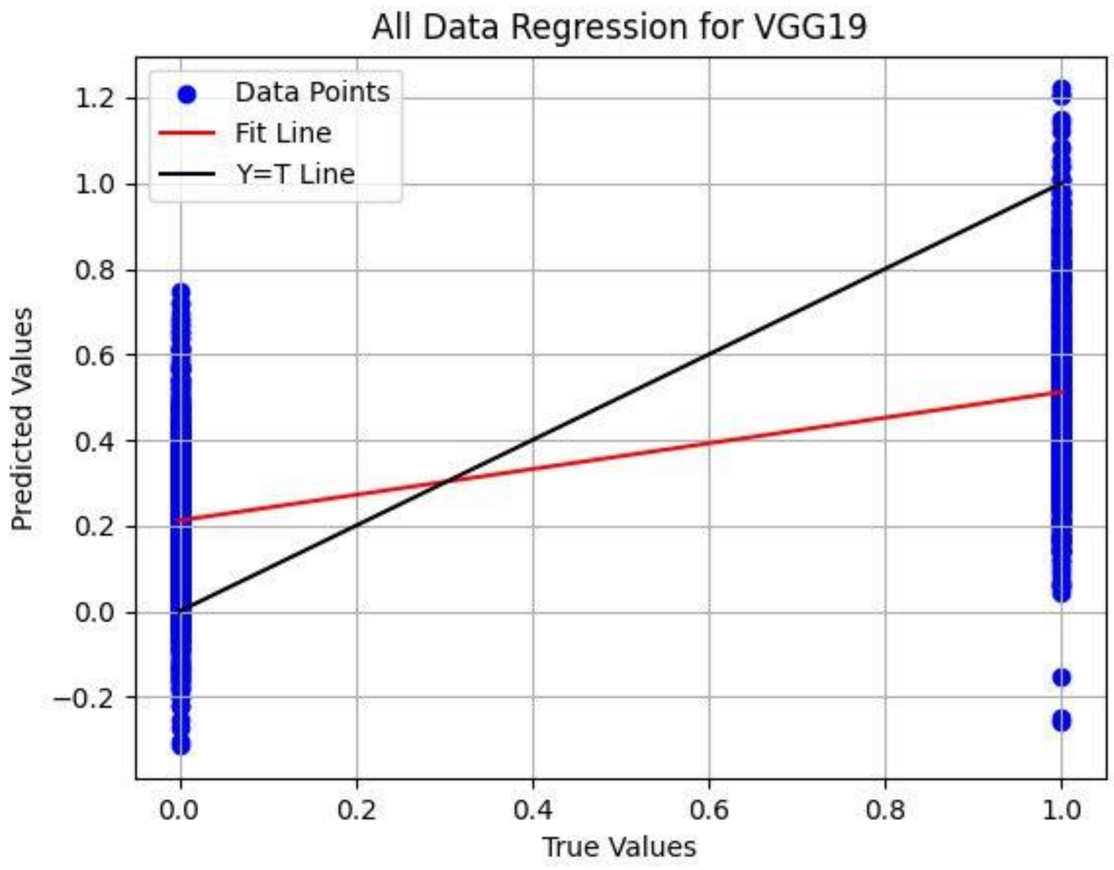

Fig. 74 All Data
Regression for VGG19

VGG19: Evaluation Metrics

Metric	Score
Accuracy	0.735294117647059
Precision	0.7434911589055
Recall	0.735294117647059
F1 Score	0.710206726133076

Fig. 75 Evaluation Metrics for VGG19

Metric	Train	Test
MSE	0.156536089760672	0.194114256963704
R2 Score	0.35826188325882	0.167793810367584

Fig. 76 Model Metrics for VGG19

ResNet50

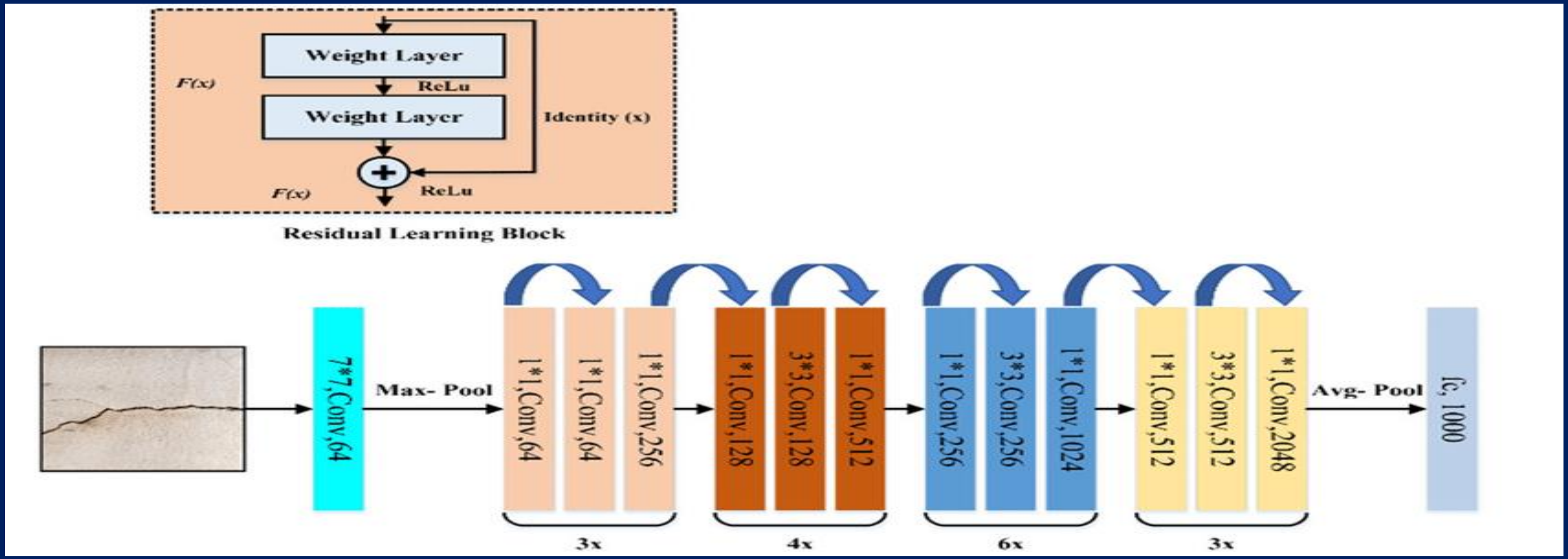

Fig. 77 ResNet50 Architecture [25]

1. Residual Connections: ResNet uses skip connections (residuals) to bypass layers, solving vanishing gradient issues.
2. Strong Performance: ResNet achieves state-of-the-art results in image classification and object detection tasks.

ResNet50

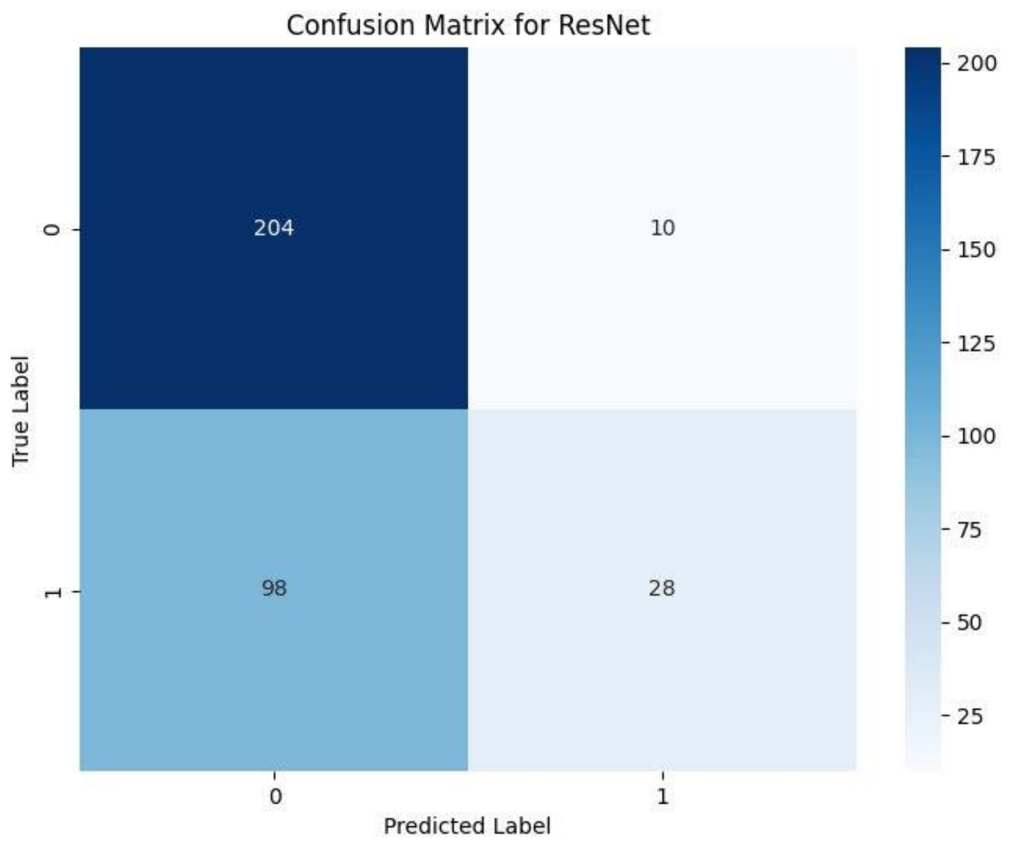

Fig. 78 Confusion Matrix for ResNet50

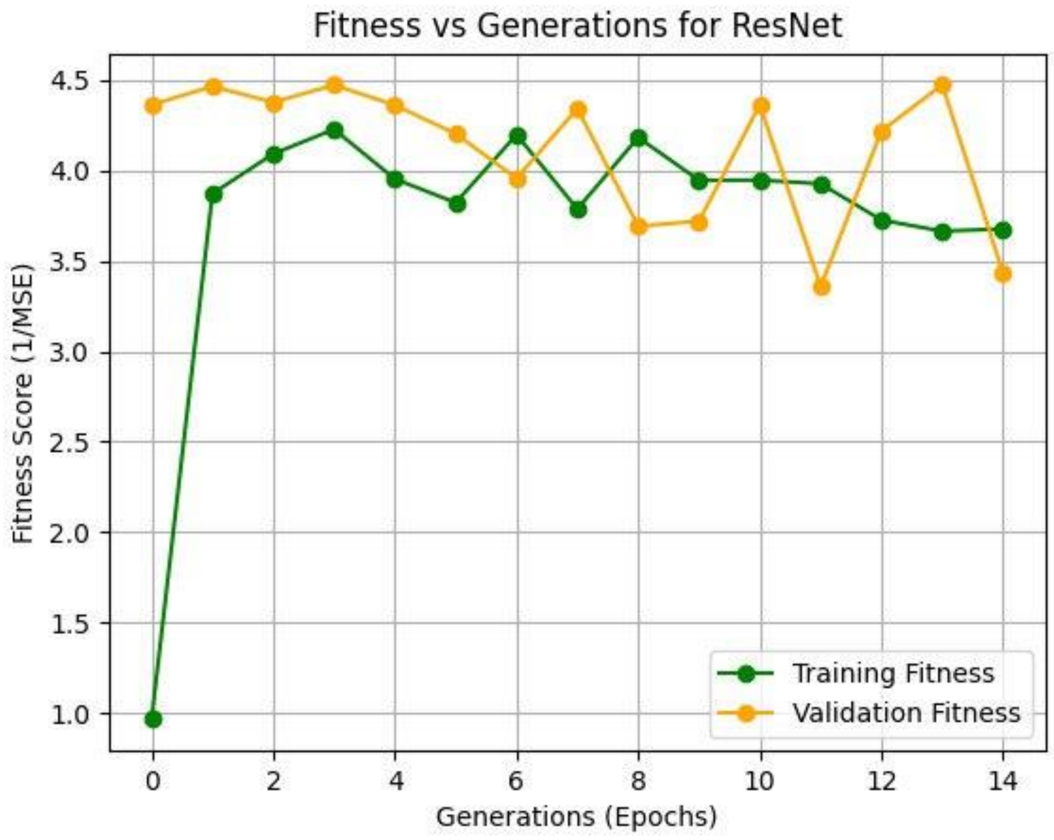

Fig. 79 Fitness vs Generations for ResNet50

ResNet50

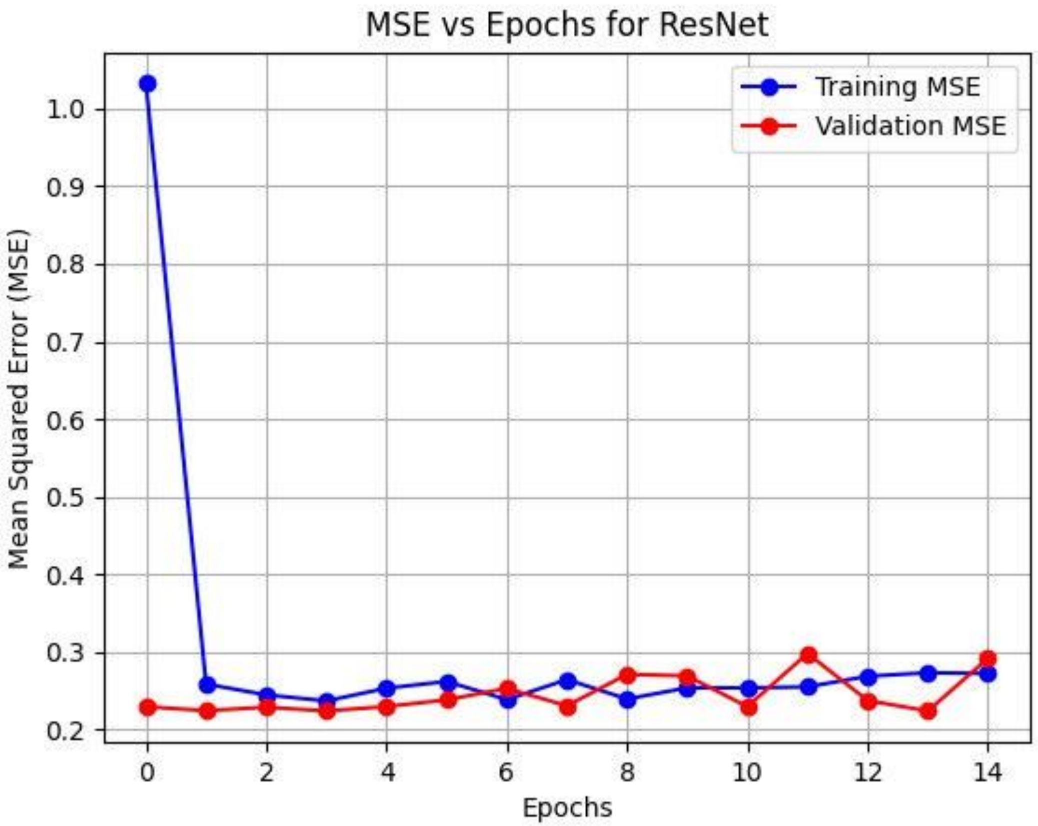

Fig. 80 MSE vs Epochs for ResNet50

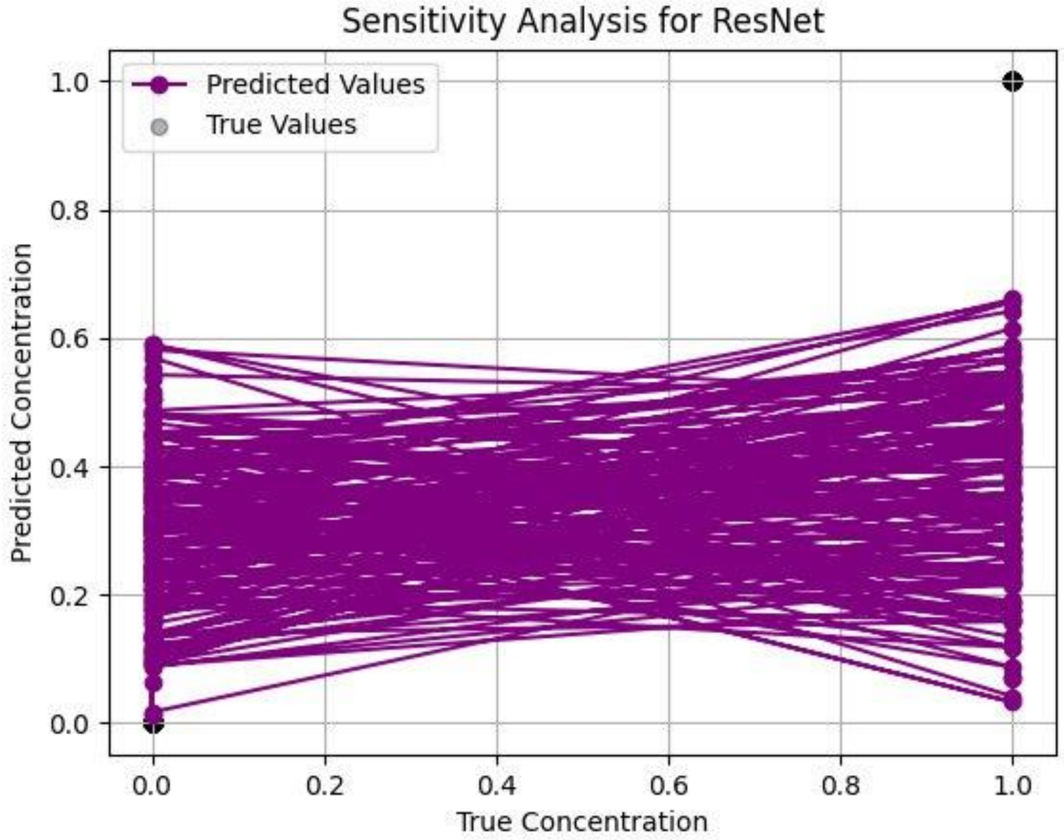

Fig. 81 Sensitivity Analysis for ResNet50

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ResNet50

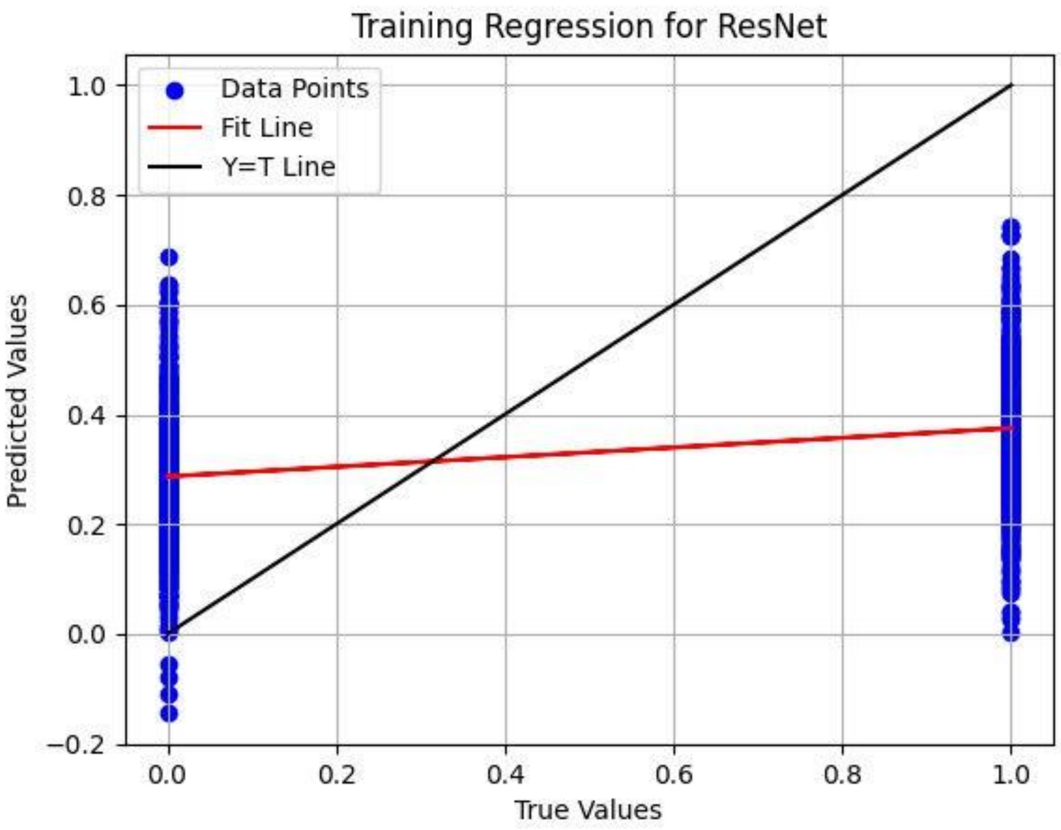

Fig. 82 Training Regression for ResNet50

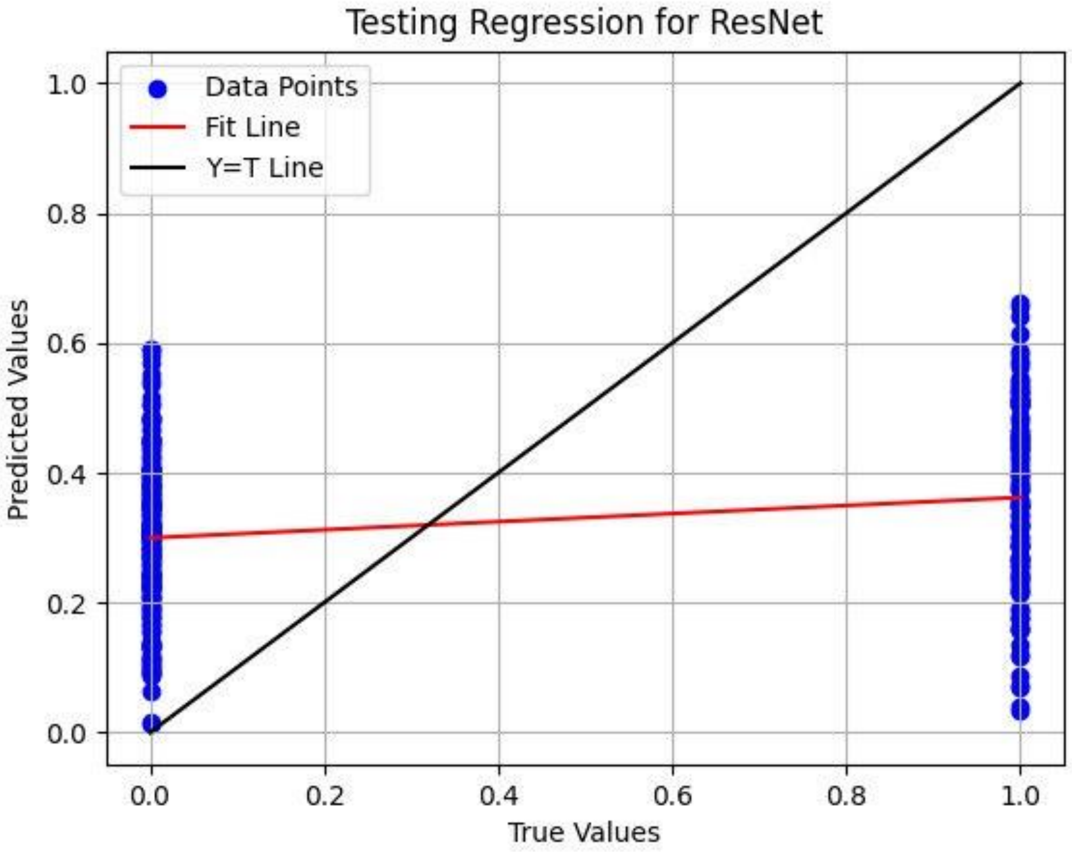

Fig. 83 Testing Regression for ResNet50

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ResNet50

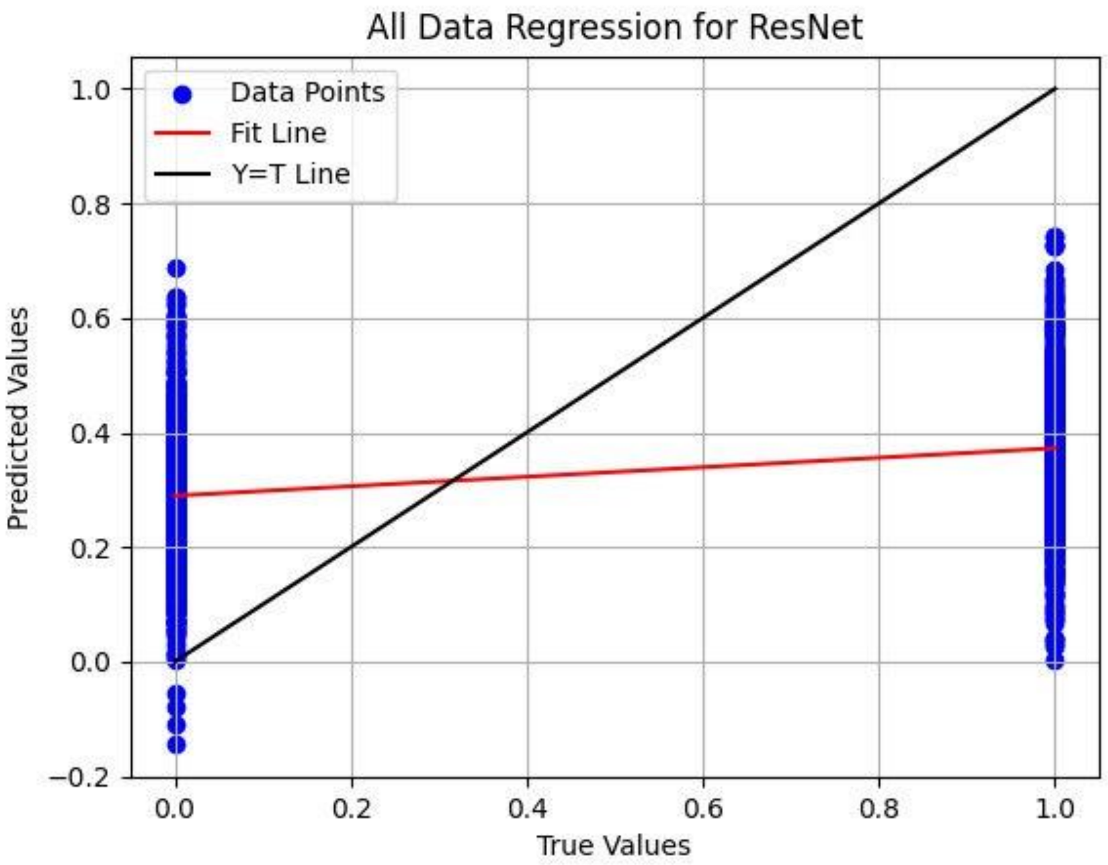

Fig. 84 All Data Regression for ResNet

ResNet50: Evaluation Metrics

Metric	Score
Accuracy	0.682352941176471
Precision	0.698230578393783
Recall	0.682352941176471
F1 Score	0.624216742851423

Fig. 85 Evaluation Metrics for ResNet50

Metric	Train	Test
MSE	0.228988089879994	0.223647188335691
R2 Score	0.0612363219261169	0.0411801934242249

Fig. 86 Model Metrics for ResNet50

All ML Models: Evaluation Metrics

Model Name	Accuracy	Precision	Recall	F1 Score
Logistic Regression	0.758823529411765	0.7430764815612	0.751298026998962	0.746139277389277
KNN	0.844117647058824	0.836476179525507	0.825582257825249	0.830305769792167
Random Forest	0.85	0.869698574517852	0.810673490580033	0.827412885310189
Decision Trees	0.697058823529412	0.677958446251129	0.682650941996736	0.679770297826425
SVM	0.820588235294118	0.822855107087472	0.785677199228601	0.797411477411477
Naive Bayes	0.461764705882353	0.651375756026919	0.565902685061564	0.424054206662902

Fig. 87 Evaluation Metrics
for all ML models

All DL Models: Evaluation Metrics

Model Name	Accuracy	Precision	Recall	F1 Score
VGG19	0.735294117647059	0.7434911589055	0.735294117647059	0.710206726133076
CNN	0.852941176470588	0.852510717548668	0.852941176470588	0.852694938440493
ResNet	0.682352941176471	0.698230578393783	0.682352941176471	0.624216742851423
RCNN	0.688235294117647	0.702289774970391	0.688235294117647	0.635868566176471
MobileNet	0.632352941176471	0.609658995272778	0.632352941176471	0.60839688892245

Fig. 88 Evaluation Metrics
for all DL models

All Models: Evaluation Metrics

Model Name	Accuracy	Precision	Recall	F1 Score	model type
Logistic Regression	0.758823529411765	0.7430764815612	0.751298026998962	0.746139277389277	ML
KNN	0.844117647058824	0.836476179525507	0.825582257825249	0.830305769792167	ML
Random Forest	0.85	0.869698574517852	0.810673490580033	0.827412885310189	ML
Decision Trees	0.697058823529412	0.677958446251129	0.682650941996736	0.679770297826425	ML
SVM	0.820588235294118	0.822855107087472	0.785677199228601	0.797411477411477	ML
Naive Bayes	0.461764705882353	0.651375756026919	0.565902685061564	0.424054206662902	ML
VGG19	0.735294117647059	0.7434911589055	0.735294117647059	0.710206726133076	DL
CNN	0.852941176470588	0.852510717548668	0.852941176470588	0.852694938440493	DL
ResNet	0.682352941176471	0.698230578393783	0.682352941176471	0.624216742851423	DL
RCNN	0.688235294117647	0.702289774970391	0.688235294117647	0.635868566176471	DL
MobileNet	0.632352941176471	0.609658995272778	0.632352941176471	0.60839688892245	DL

Fig. 89 Evaluation Metrics
for all models

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