

PREDICTIVE ANALYTICS LAB PROJECT

Project Report for Kidney Stone Detection Using Machine Learning and Deep Learning Techniques

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1. INTRODUCTION

1.1 Purpose of the Project

- The primary purpose of this project is to harness the power of machine learning to address the challenges associated with kidney stone diagnosis. Traditional methods of detecting kidney stones, while effective, often require significant time, expertise, and manual effort. This project aims to automate the diagnostic process by building a robust image classification model that distinguishes between normal kidney images and those with stones. By enhancing diagnostic accuracy and efficiency, the project seeks to reduce human error, support faster decision-making, and improve patient outcomes. Additionally, it aims to serve as a stepping stone for future advancements in medical imaging and AI-based healthcare solutions.

1.2 Target Beneficiary

- **Healthcare Professionals:** The project will assist doctors and radiologists by providing a reliable, automated diagnostic tool. It will reduce the cognitive load of manually interpreting medical images, saving time and improving accuracy, especially in resource-constrained settings.
- **Patients:** Patients will benefit from faster and more accurate diagnoses, enabling earlier intervention and treatment. This can significantly reduce complications and improve recovery rates for individuals with kidney stones.
- **Healthcare Systems:** The automated system will streamline diagnostic workflows in clinics and hospitals, reducing reliance on manual labor and cutting costs associated with prolonged diagnostic procedures. It will also enhance the scalability of healthcare services by handling a large volume of cases efficiently.
- **Research and Academic Community:** The project can serve as a benchmark for future research in AI-based medical diagnostics, offering insights into the application of machine learning in detecting kidney-related conditions.

1.3 Project Scope

- **Dataset Preparation:** The project will involve curating and pre-processing a dataset of medical images divided into two classes: Normal (healthy kidneys) and Stone (kidneys with stones). The quality and diversity of the dataset will be key to ensuring the model's robustness.

- **Model Development:** The scope includes implementing and training various machine learning algorithms such as Random Forest, Support Vector Machine (SVM), Logistic Regression, and Decision Tree. The models will be evaluated based on performance metrics such as accuracy, precision, recall, and F1-score to identify the most effective one.
- **Automation of Detection:** An end-to-end system will be developed to automate the process of uploading medical images, classifying them into the appropriate category, and generating real-time predictions. This system will be designed to work seamlessly in clinical environments.
- **Performance Optimization:** The models will be fine-tuned using hyperparameter optimization techniques and validated on unseen data to ensure they are robust and generalize well across different scenarios.
- **Deployment Potential:** While the initial implementation will focus on research and development, the system will be designed with deployment in mind, making it suitable for integration into hospital workflows or standalone diagnostic tools.
- **Future Expansion:** The project provides a foundation for future enhancements, such as incorporating multi-class classification for detecting other kidney-related conditions, integrating with advanced diagnostic tools, or expanding to include 3D imaging data for better accuracy. It can also be adapted for detecting conditions in other organs, showcasing its versatility.

2. PROJECT DESCRIPTION

2.1 SWOT Analysis

- **Strengths:**
 - Utilizes machine learning to automate kidney stone detection, reducing reliance on manual interpretation.
 - Implements multiple models (Random Forest, SVM, Logistic Regression, Decision Tree) to identify the most accurate solution.
 - Enhances diagnostic accuracy and efficiency, improving patient care.
 - Offers scalability for high-volume medical imaging applications.
- **Weaknesses:**
 - Limited availability of diverse and high-quality labeled datasets may restrict model generalization.
 - Requires significant computational resources for model training and testing.
 - Real-time predictions might demand trade-offs between speed and accuracy.
 - Ethical and regulatory compliance could delay deployment.

- **Opportunities:**

- Potential to integrate with hospital management systems and diagnostic tools for seamless operation.
- Scope for extending the model to detect other kidney conditions or organ-related issues.
- Advancements in AI and deep learning can further enhance system performance.
- Contributes to the growing field of AI-driven healthcare solutions.

- **Threats:**

- High dependency on data quality; poor image resolution may lead to inaccurate predictions.
- Competition from other AI-driven diagnostic tools in the healthcare sector.
- Regulatory barriers and ethical concerns related to patient data usage.
- Resistance to adoption due to trust issues in automated systems.

2.2 Project Features

- **Binary Classification System:** Distinguishes between Normal (healthy kidneys) and Stone (kidneys with stones) using medical images.
- **Model Diversity:** Implements multiple machine learning models, including Random Forest, SVM, Logistic Regression, and Decision Tree, for comparison and performance optimization.
- **Automated Detection:** Provides a fully automated system for real-time prediction, reducing manual diagnostic efforts.
- **Performance Metrics Evaluation:** Measures accuracy, precision, recall, F1-score, and runtime to identify the most effective model.
- **Scalable Design:** Capable of handling a large volume of medical images for high-demand clinical environments. **User-Friendly Interface:** Simple interface allowing healthcare professionals to upload images and receive instant results.
- **Extensibility:** Designed to accommodate future enhancements, such as multi-class classification or integration with advanced imaging techniques like 3D scans.
- **Compliance Focus:** Ensures adherence to privacy and ethical standards for medical data usage.

These features make the project a comprehensive solution for automated kidney stone detection, addressing both practical and technological needs.

2.3 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

S. No.	Authors	Title	Journal/Conference	Year	Key Focus	Major Findings
						kidney stone diagnosis.
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.

S. No.	Authors	Title	Journal/Conference	Year	Key Focus	Major Findings
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.
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	Contrast-Enhanced Medical MRI Evaluation Using Tsallis Entropy and Region	Journal of Ambient Intelligence and Humanized Computing	2018	MRI image evaluation using contrast enhancement	Applied Tsallis entropy for better segmentation and evaluation

S. No.	Authors	Title	Journal/Conference	Year	Key Focus	Major Findings
	Satapathy, V. Rajinikanth	Growing Segmentation ^[13]				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

2.4 Project Code

Github Link: https://github.com/kavyadangi/Kidney_Stone_Detection/tree/main/codes

2.5 Design and Implementation Constraints

The following constraints may impact the design and implementation of the kidney stone detection system:

1. Data-Related Constraints:

- Limited Dataset Availability: Access to a large, diverse, and labeled dataset of kidney images is critical for training machine learning models. Insufficient data or class imbalance could affect model accuracy.
- Data Quality: The quality of medical images, such as resolution and noise levels, can impact the model's ability to correctly classify images.

2. Computational Constraints:

- High Resource Requirements: Training machine learning models, especially on high-resolution images, requires substantial computational power (e.g., GPUs). Limited resources can slow down the development process.

- **Model Complexity:** Advanced models like deep neural networks may demand more memory and processing power, which may not be feasible for deployment on low-end systems.

3. Time Constraints:

- **Development Timeline:** Limited time for designing, training, and testing multiple models might restrict the scope for extensive hyperparameter tuning or advanced optimization techniques.
- **Real-Time Predictions:** The system must be designed to provide predictions in real-time, which could necessitate trade-offs between accuracy and speed.

4. Ethical and Regulatory Constraints: Data Privacy:

- Ensuring that medical images comply with data privacy laws (e.g., HIPAA, GDPR) and maintaining patient confidentiality throughout the project.
- **Regulatory Compliance:** The system may need to meet specific standards for medical device software if intended for clinical use.

5. Deployment Constraints: Hardware Limitations:

- The final system may be required to run on standard hospital infrastructure, which might limit the use of computationally heavy models.
- **Scalability:** The system must handle varying workloads, especially in hospitals or clinics with a high patient volume, requiring efficient design and optimization.

6. Model Performance Constraints:

- **Generalization:** The model must generalize well across diverse patient demographics, imaging conditions, and devices to avoid biases.
- **False Positives/Negatives:** Minimizing incorrect classifications is crucial, as false negatives could delay treatment, and false positives might lead to unnecessary interventions. By acknowledging these constraints, the system design will focus on achieving a balance between performance, reliability, and practicality.

2.6 Output

Data Analysis

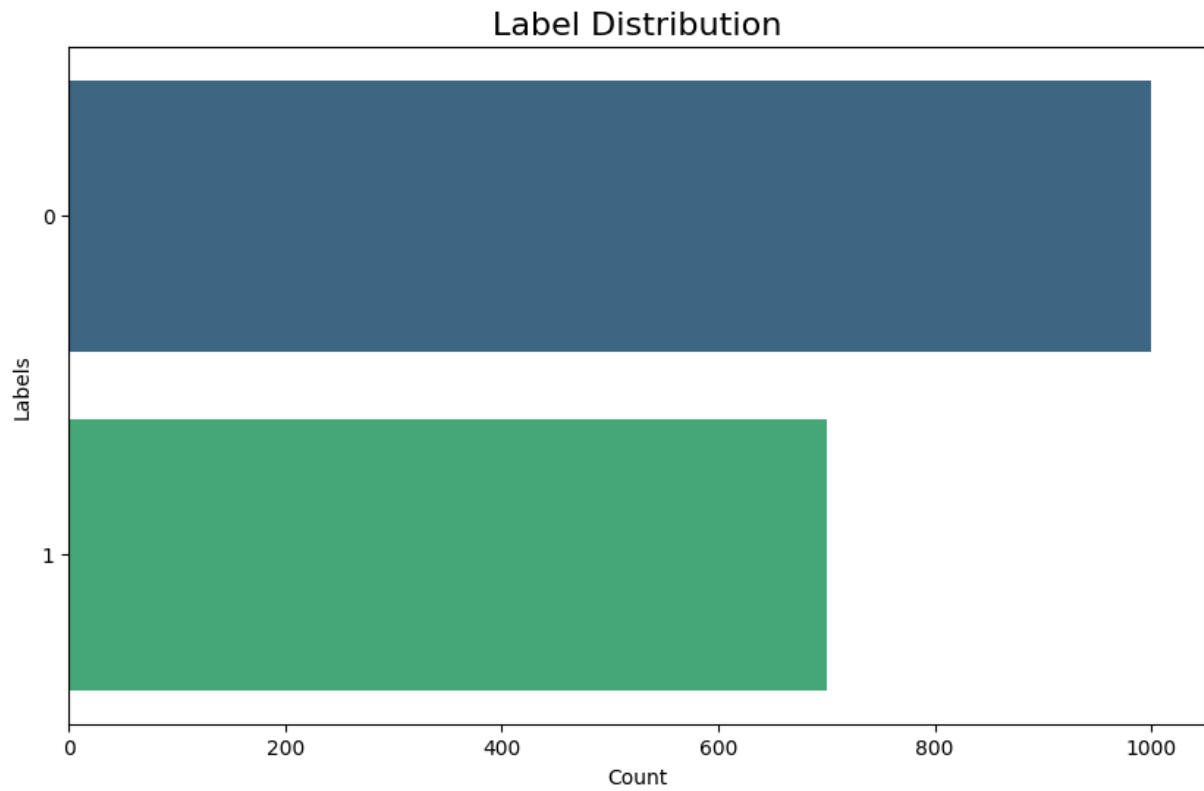


Fig. 1 Label Distribution



Fig. 2 Heatmap of Label Counts

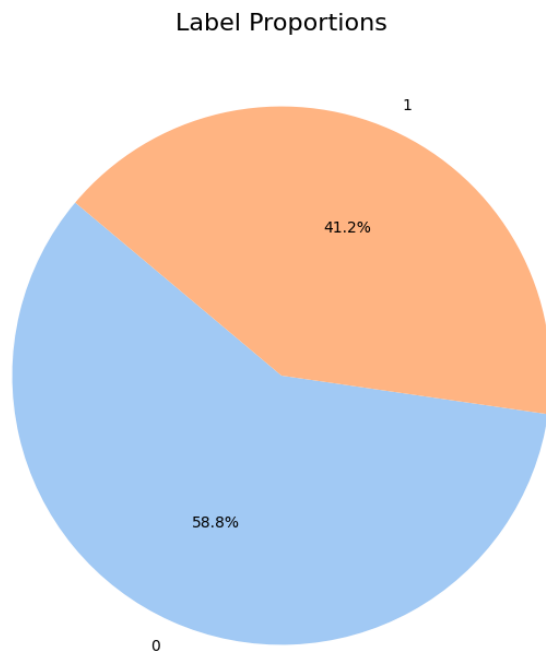


Fig. 3 Label Proportions

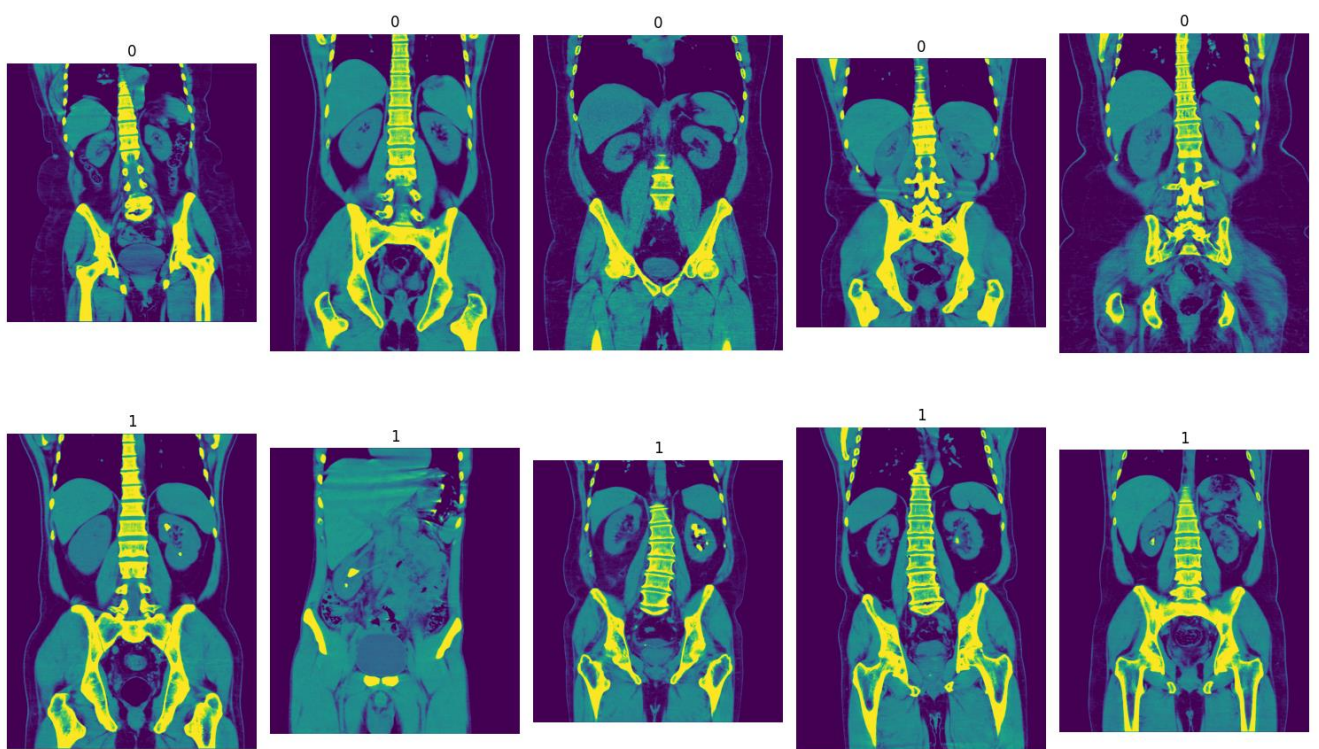


Fig. 4 Example Images

Machine Learning Techniques

Logistic Regression:

Fitness Function (Logistic Regression Accuracy Over Regularization Strength)

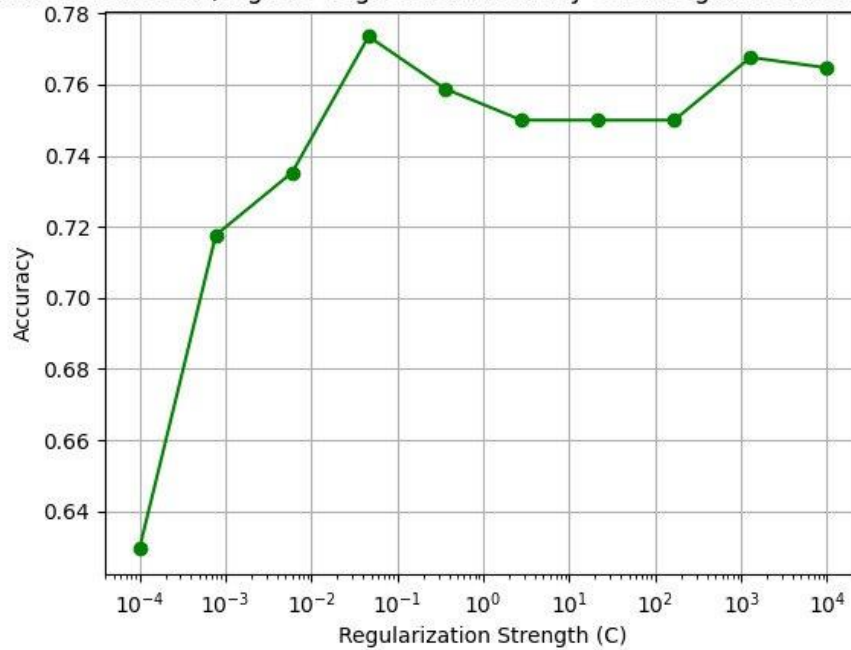


Fig. 5 Fitness Function for Logistic Regression

Training Regression (Logistic Regression)

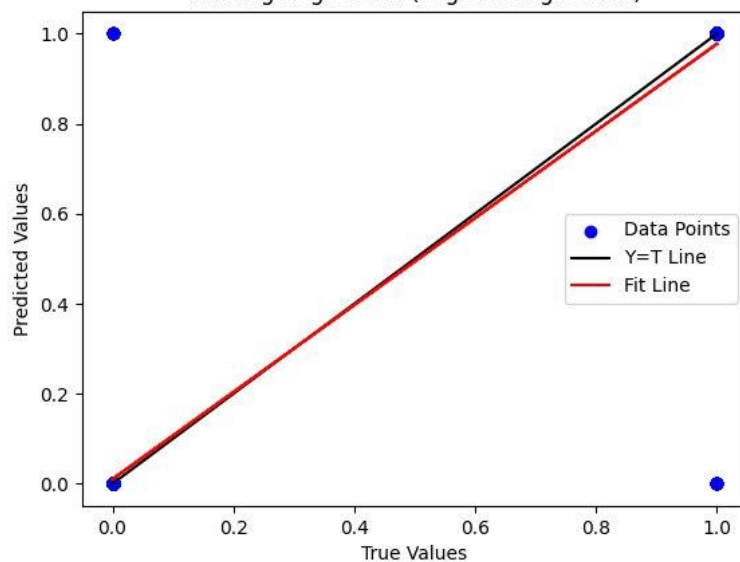


Fig. 6 Training Regression for Logistic Regression

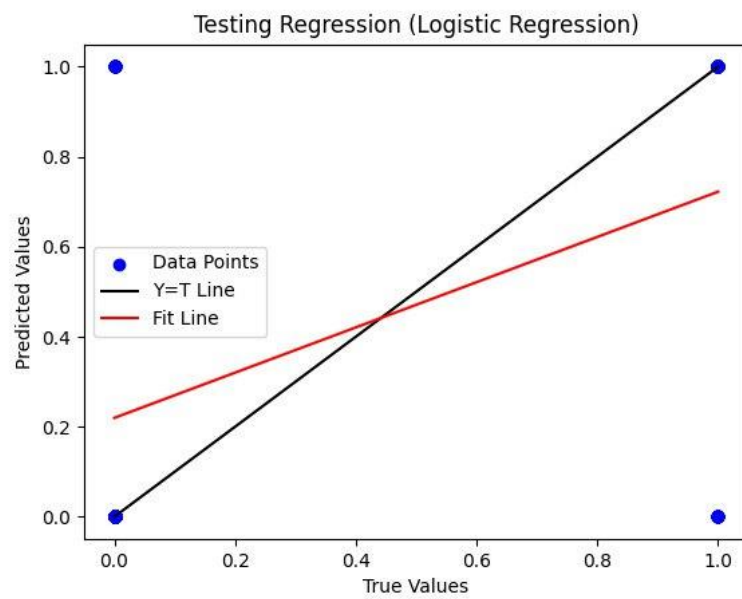


Fig. 7 Testing Regression for Logistic Regression

Metric	Value
Accuracy	0.758823529411765
Precision	0.7430764815612
Recall	0.751298026998962
F1 Score	0.746139277389277

Fig. 8 Evaluation Metrics for Logistic Regression

Naïve Bayes

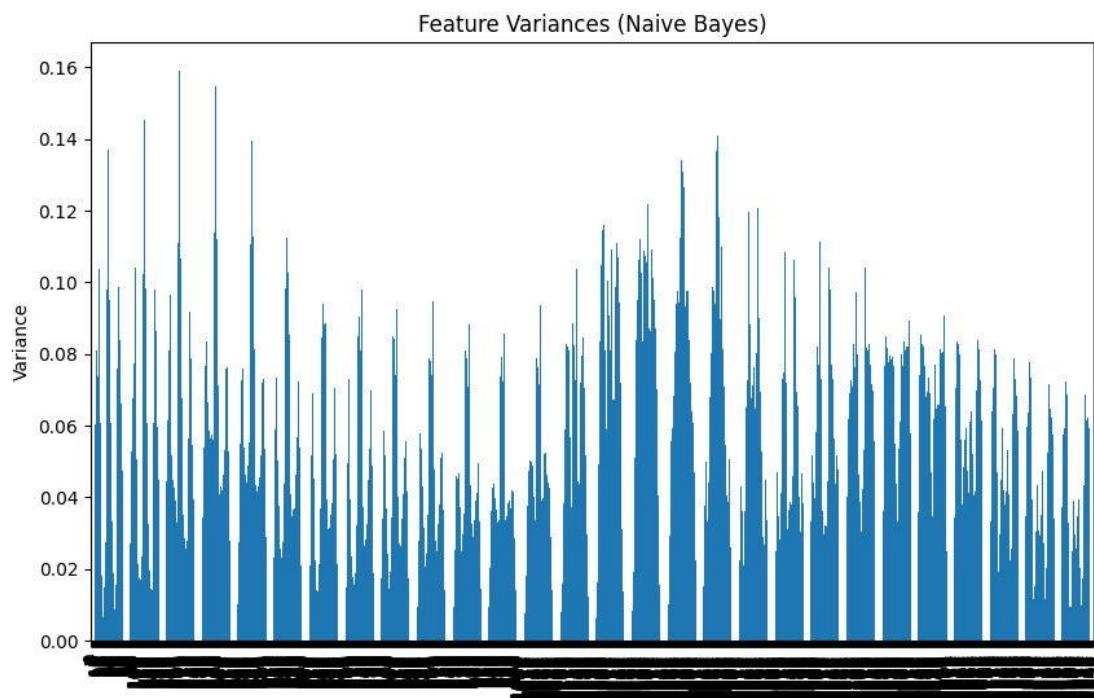


Fig. 9 Feature Variances for Naïve Bayes

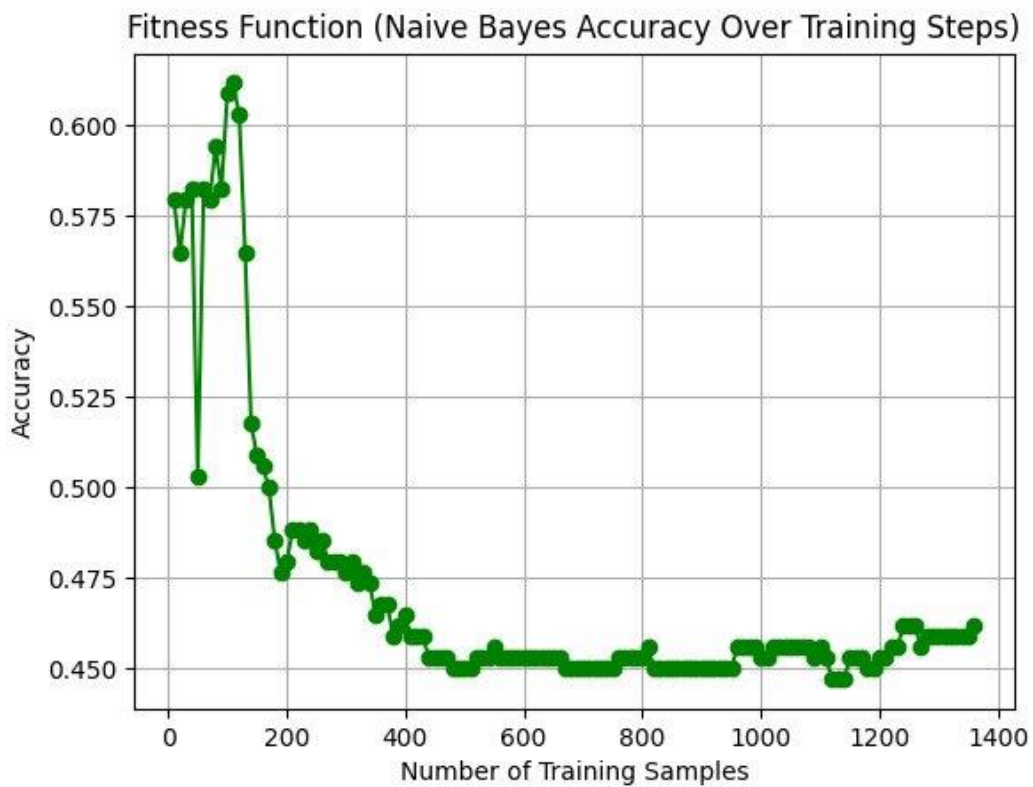


Fig. 10 Fitness Function for Naïve Bayes

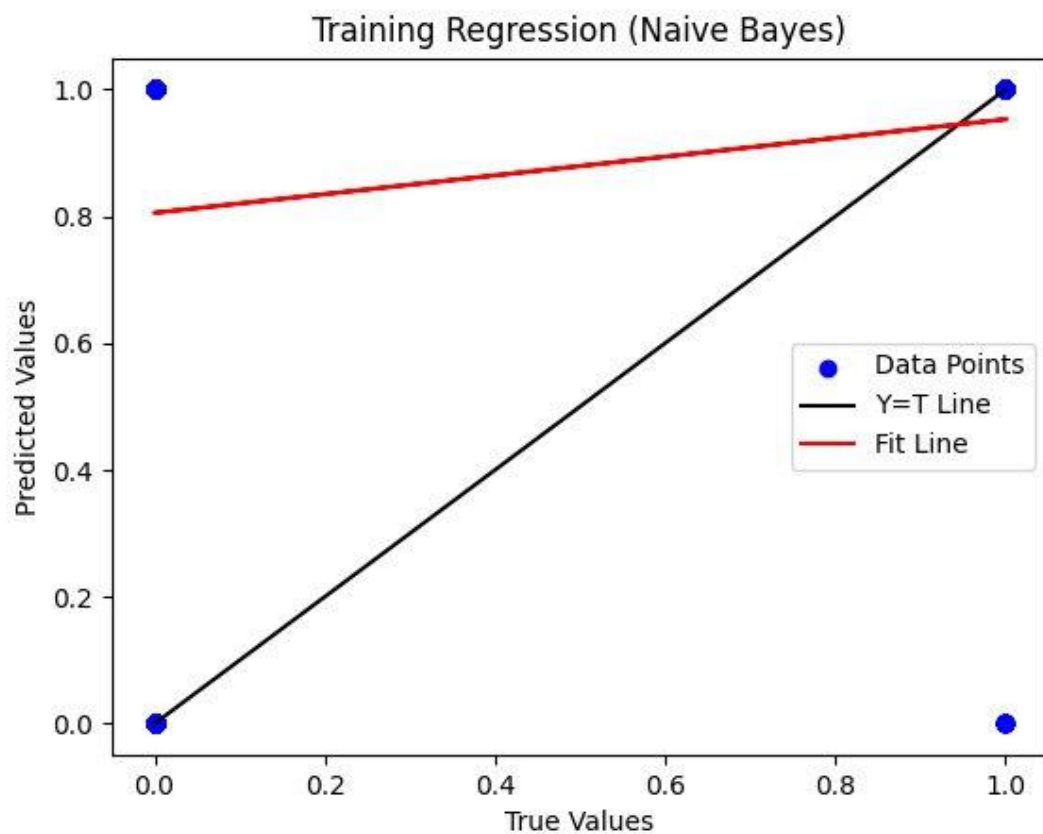


Fig. 11 Training Regression for Naïve Bayes

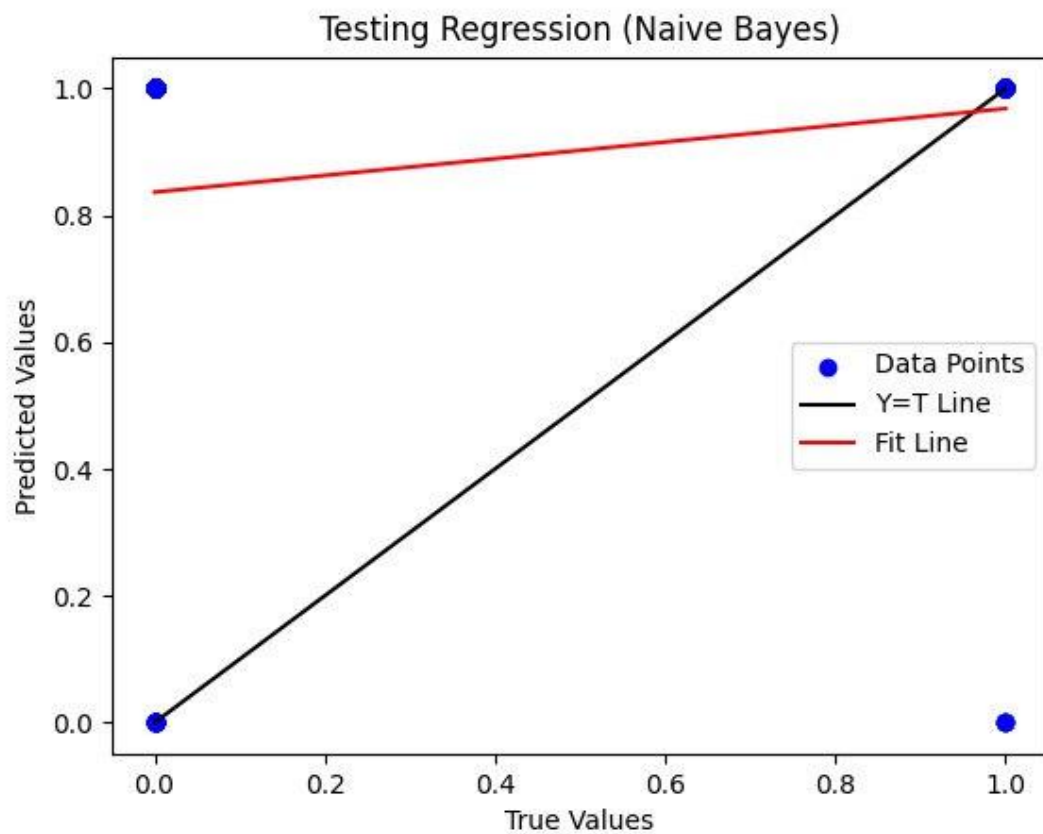
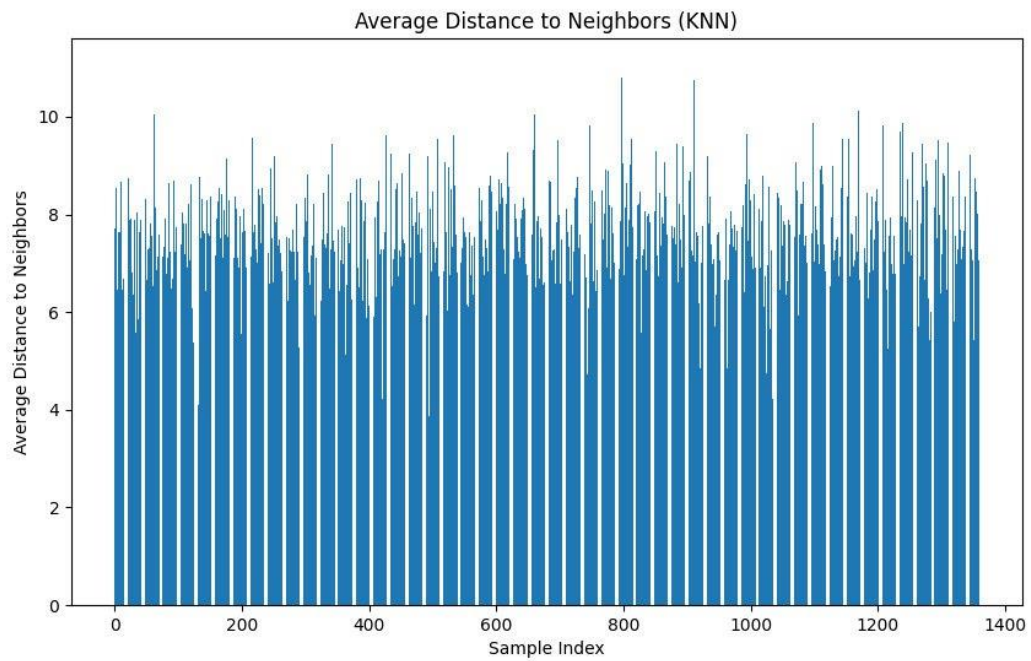


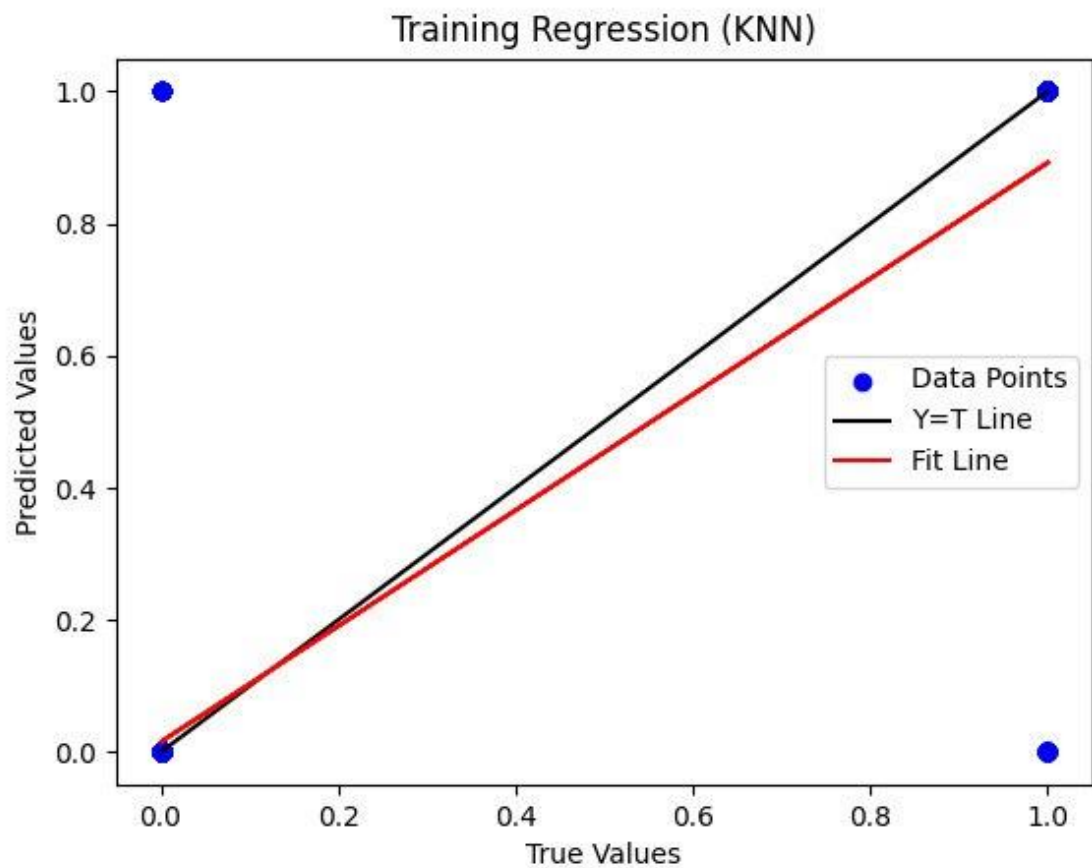
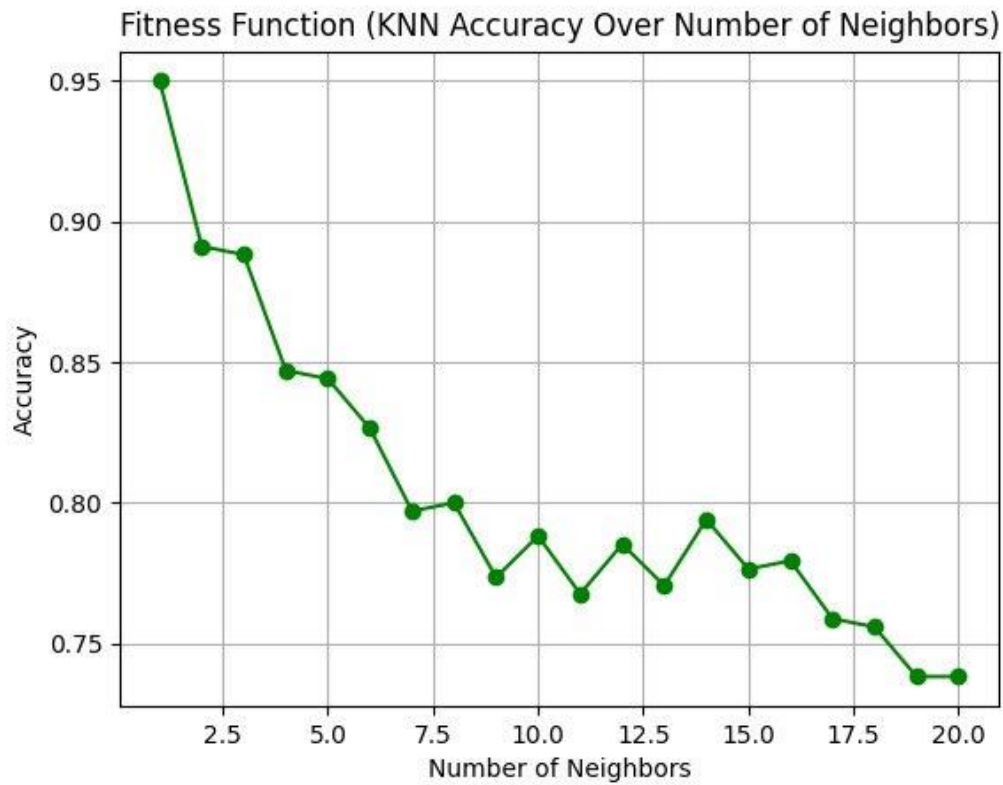
Fig. 12 Testing Regression for Naïve Bayes

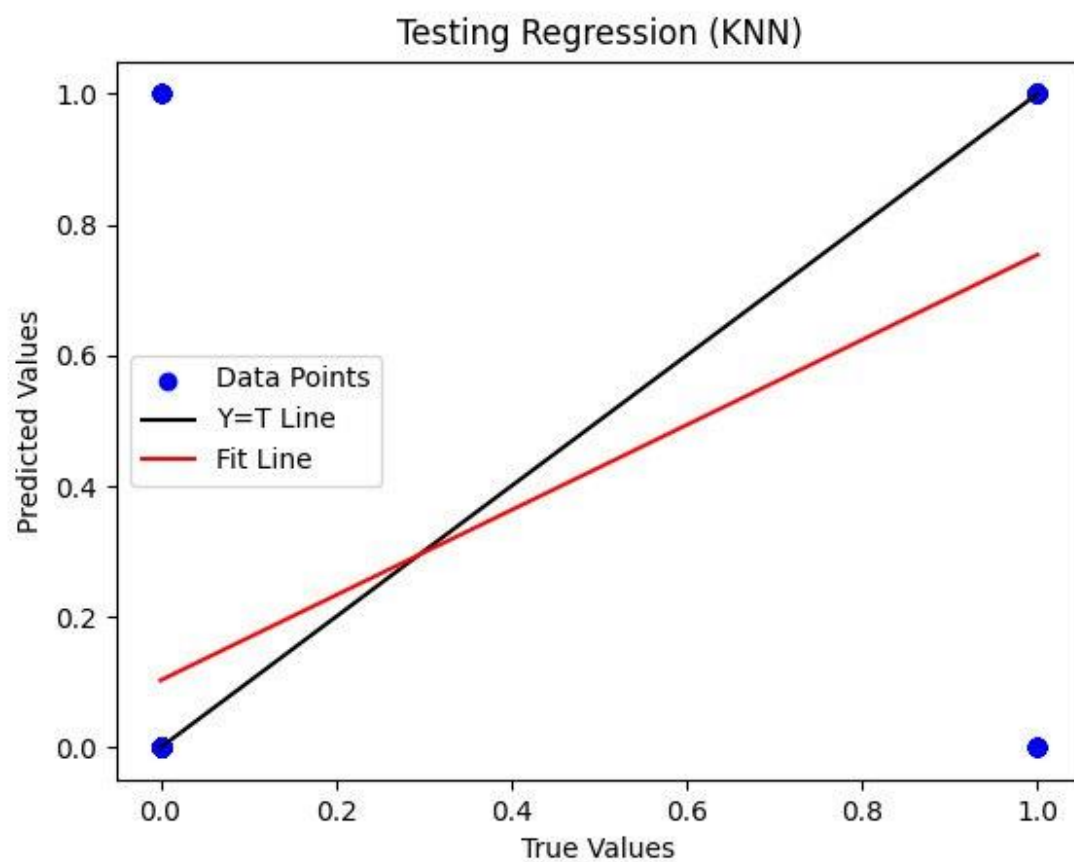
Metric	Value
Accuracy	0.461764705882353
Precision	0.651375756026919
Recall	0.565902685061564
F1 Score	0.424054206662902

Fig. 13 Evaluation Metrics for Naïve Bayes

K Nearest Neighbour

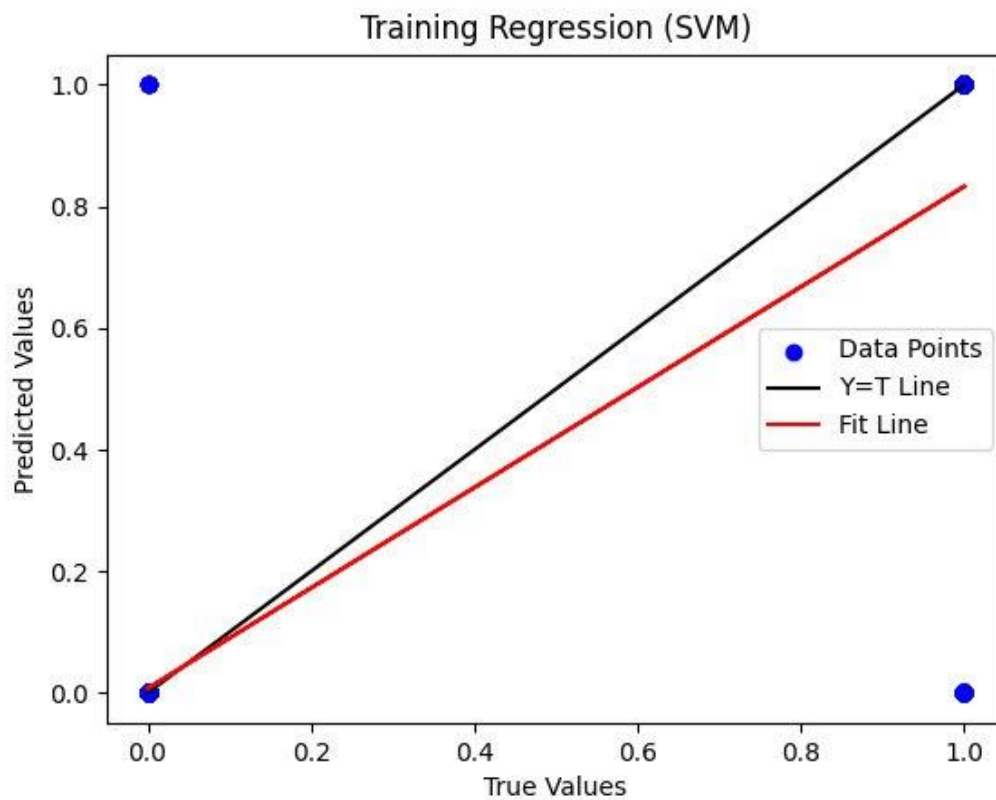
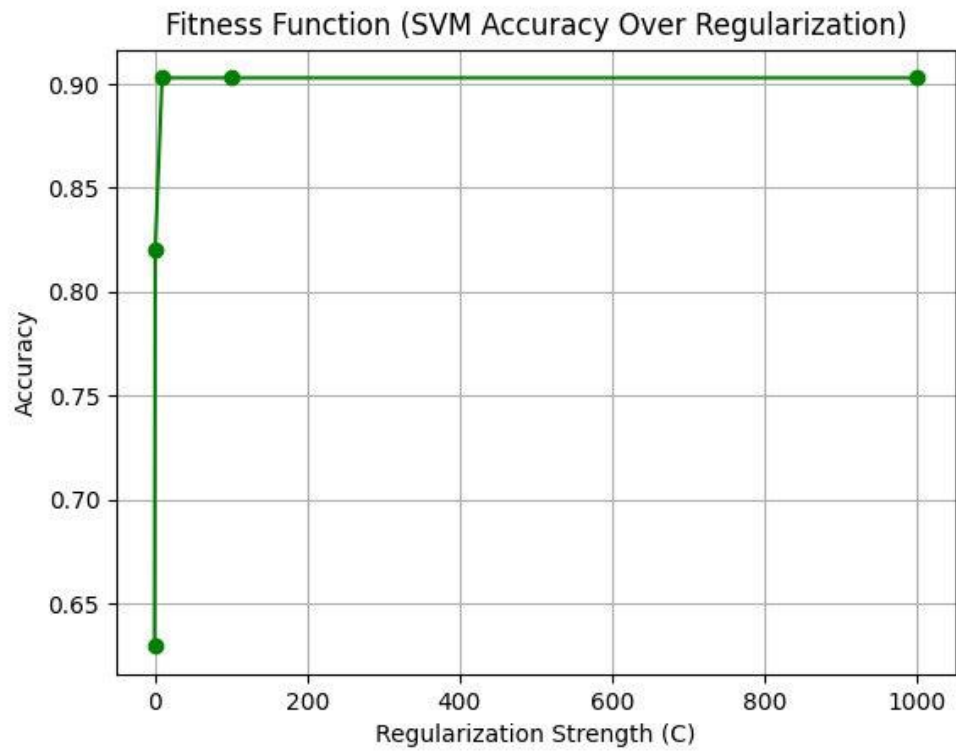


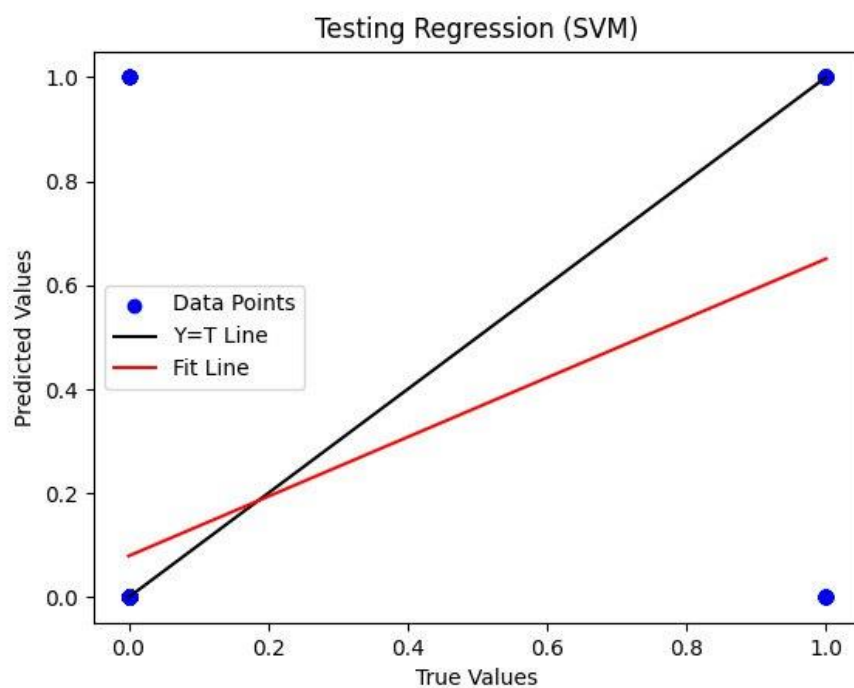




Metric	Value
Accuracy	0.844117647058824
Precision	0.836476179525507
Recall	0.825582257825249
F1 Score	0.830305769792167

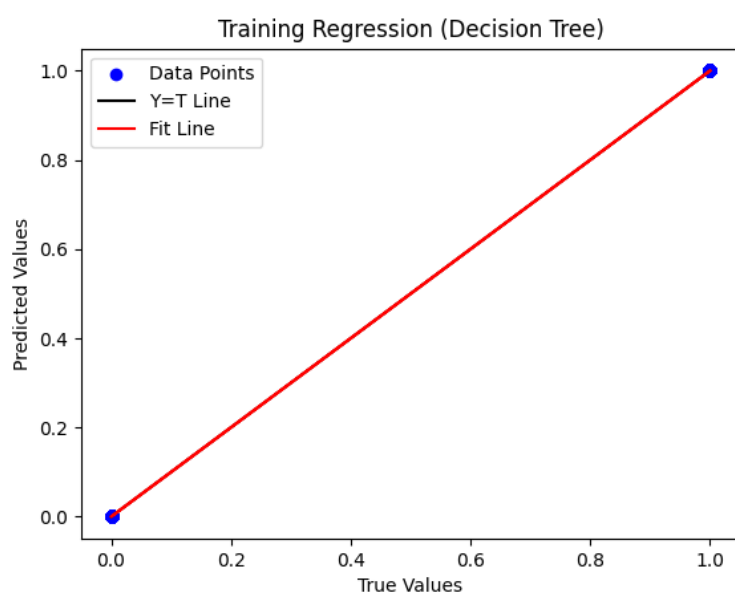
Support Vector Machine

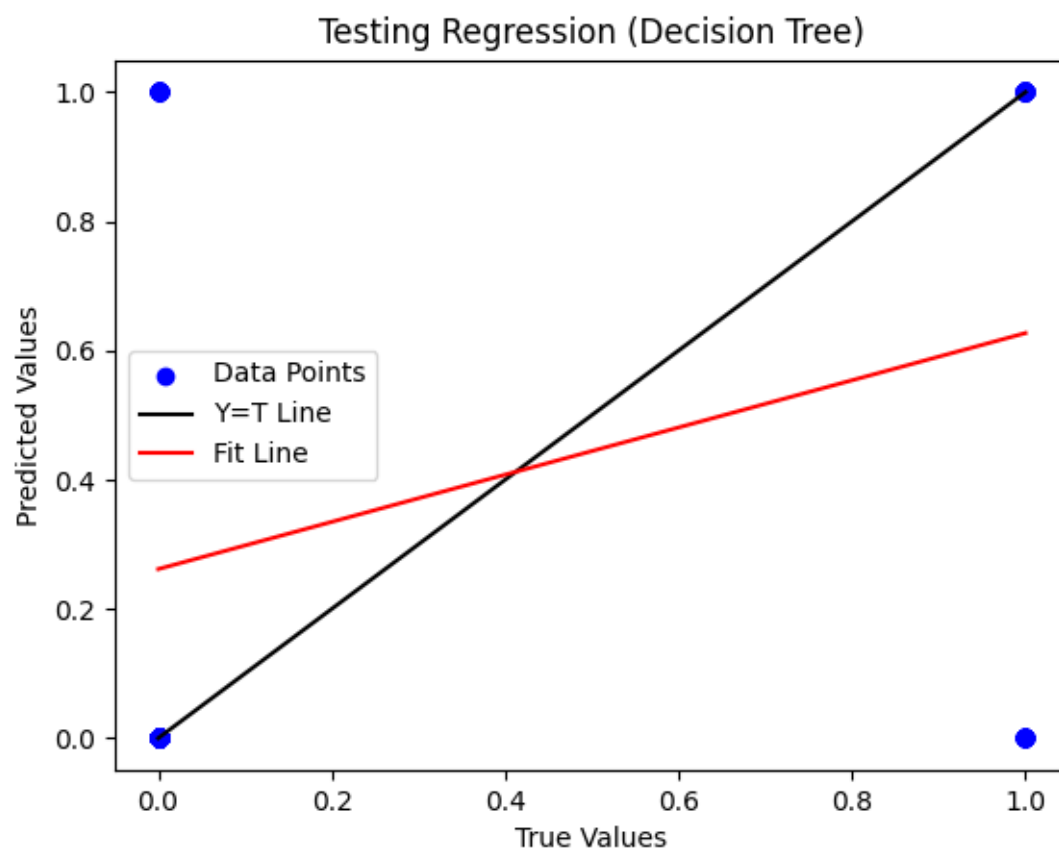




Metric	Value
Accuracy	0.820588235294118
Precision	0.822855107087472
Recall	0.785677199228601
F1 Score	0.797411477411477

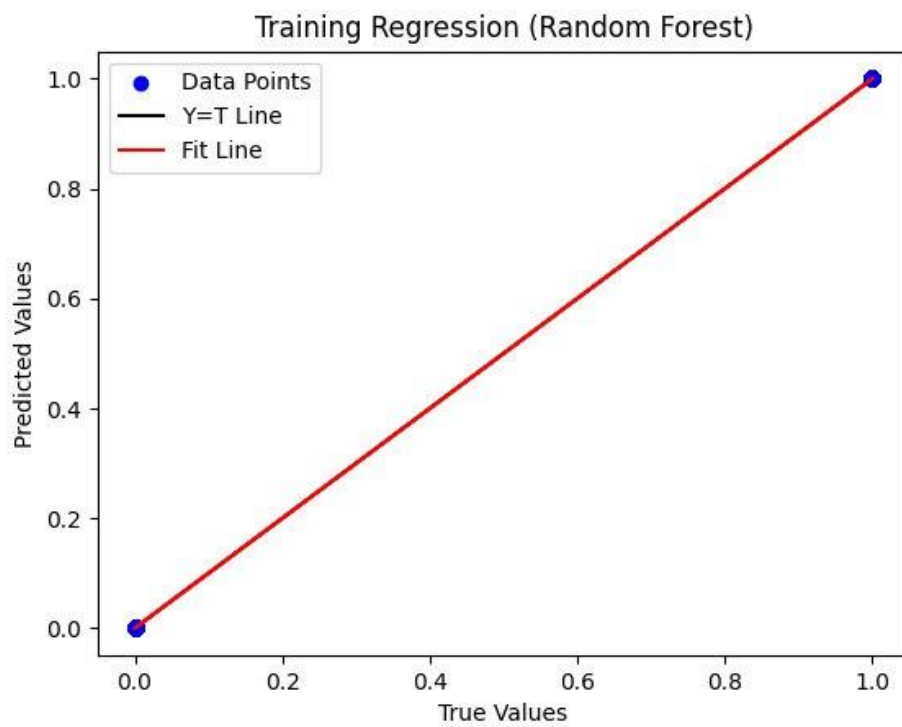
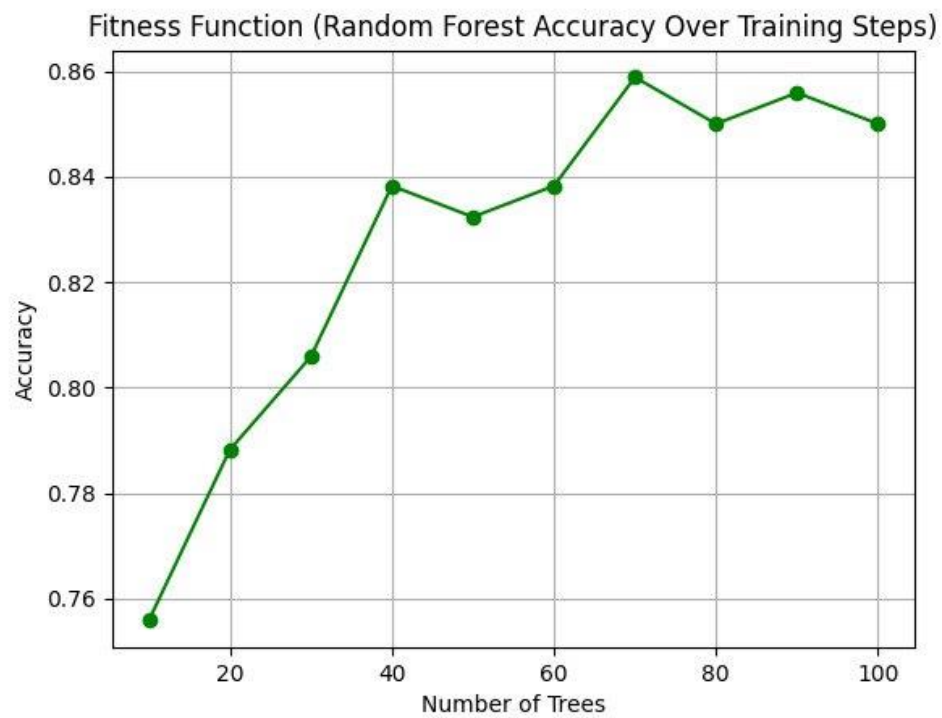
Decision Tree

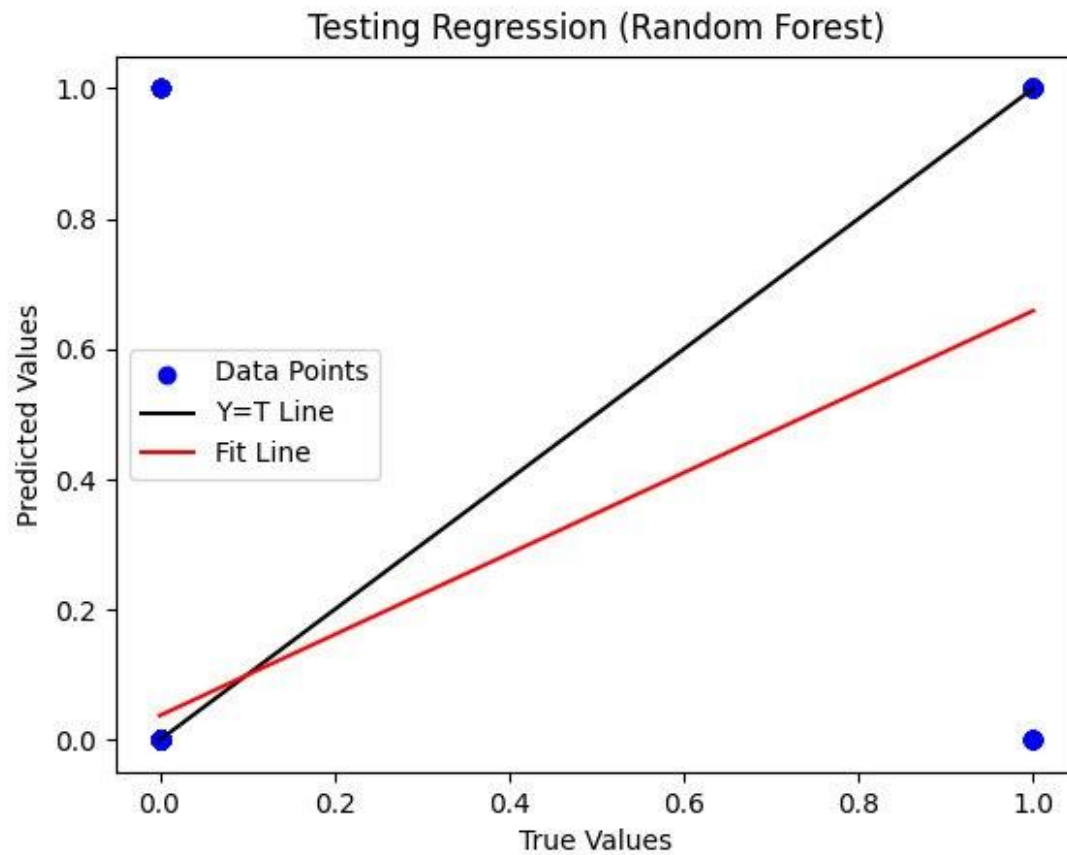




Metric	Value
Accuracy	0.697058823529412
Precision	0.677958446251129
Recall	0.682650941996736
F1 Score	0.679770297826425

Random Forest





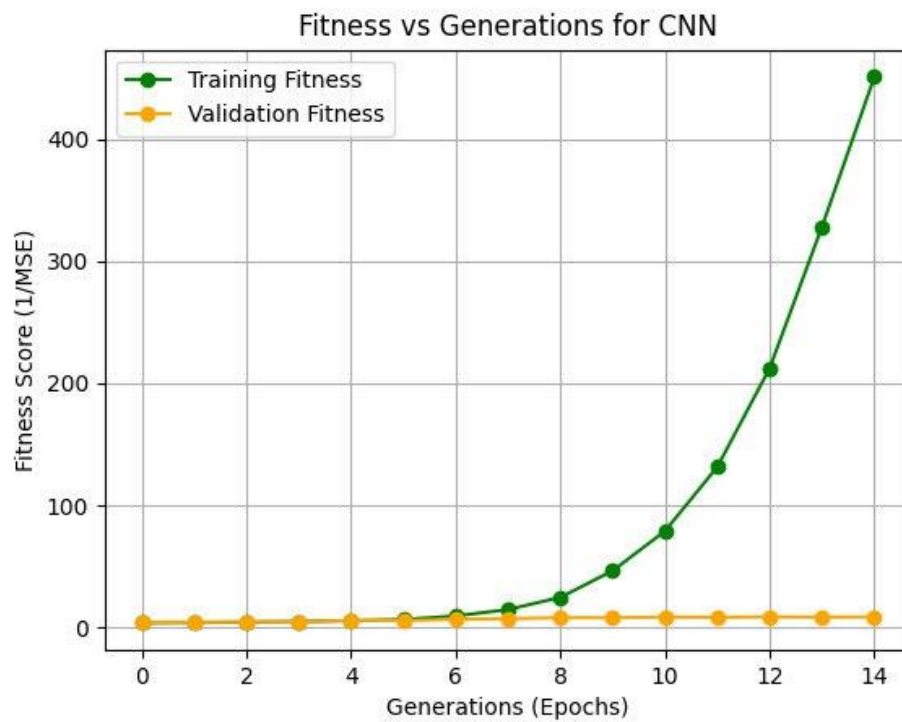
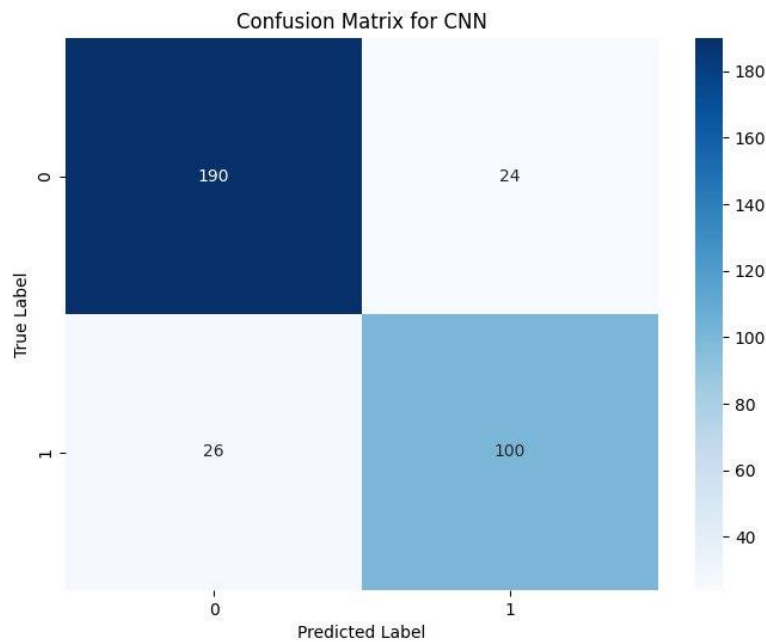
Metric	Value
Accuracy	0.85
Precision	0.869698574517852
Recall	0.810673490580033
F1 Score	0.827412885310189

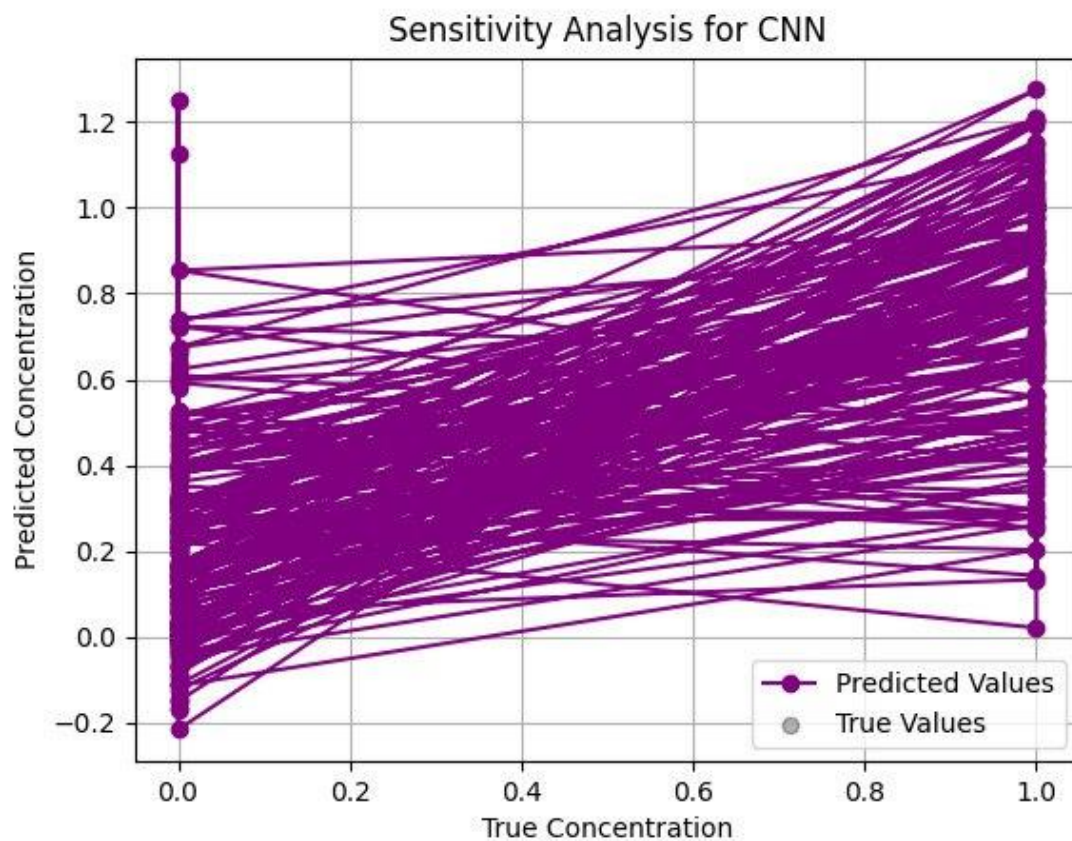
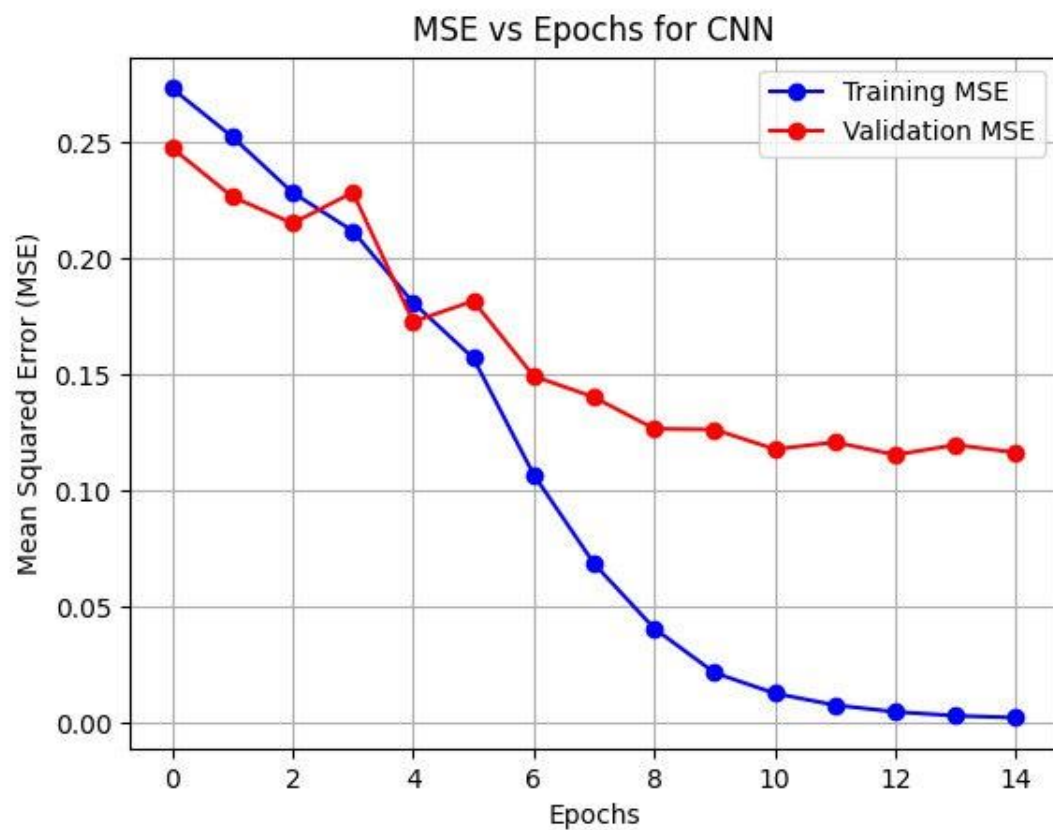
Model Name	Accuracy	Precision	Recall	F1 Score
Logistic Regression	0.758823529411765	0.7430764815612	0.751298026998962	0.746139277389277
KNN	0.844117647058824	0.836476179525507	0.825582257825249	0.830305769792167
Random Forest	0.85	0.869698574517852	0.810673490580033	0.827412885310189
Decision Trees	0.697058823529412	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

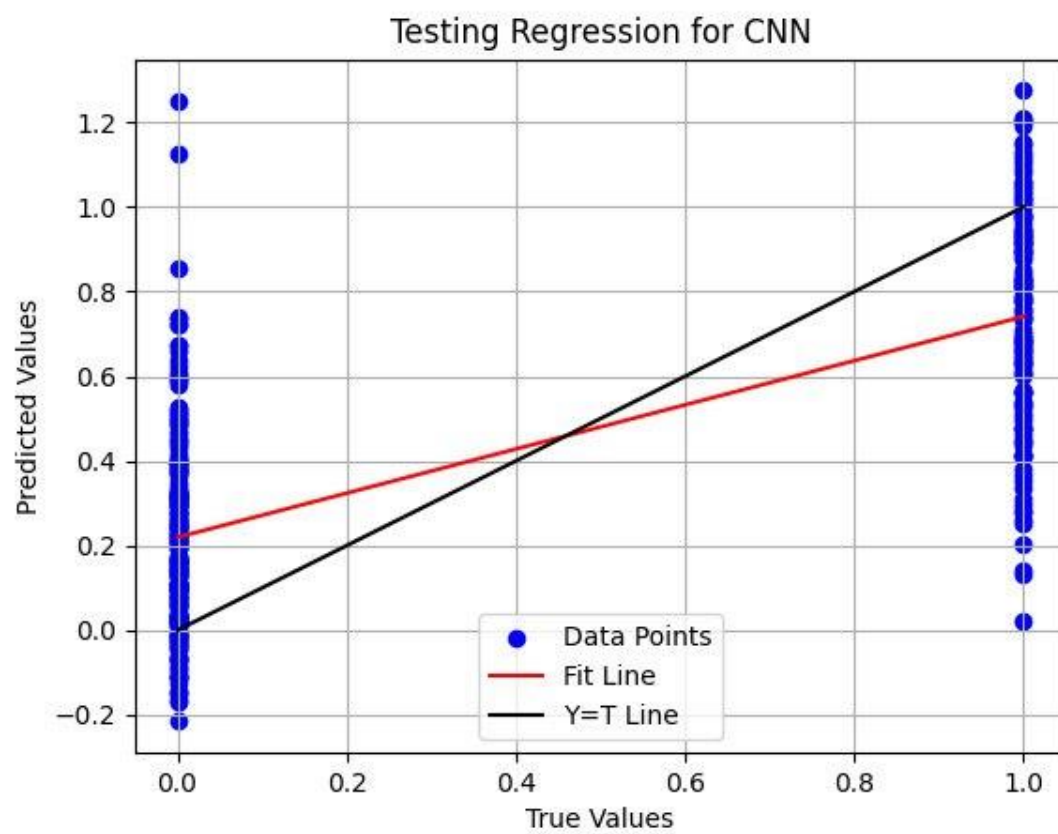
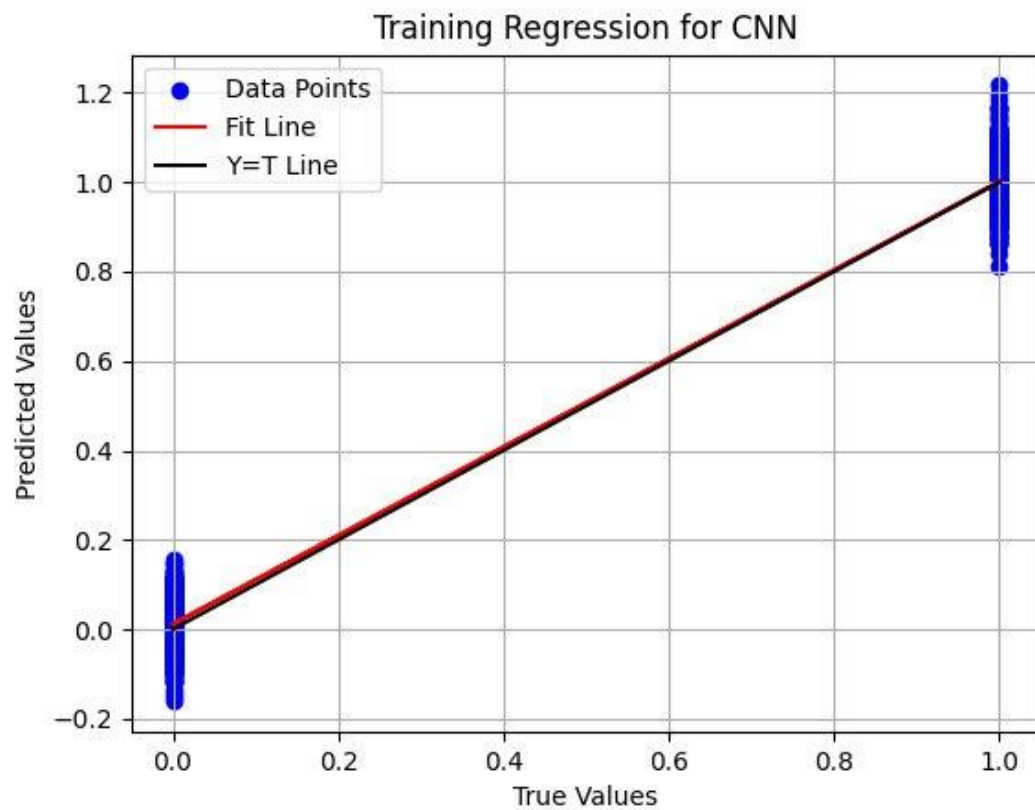
All ML Models

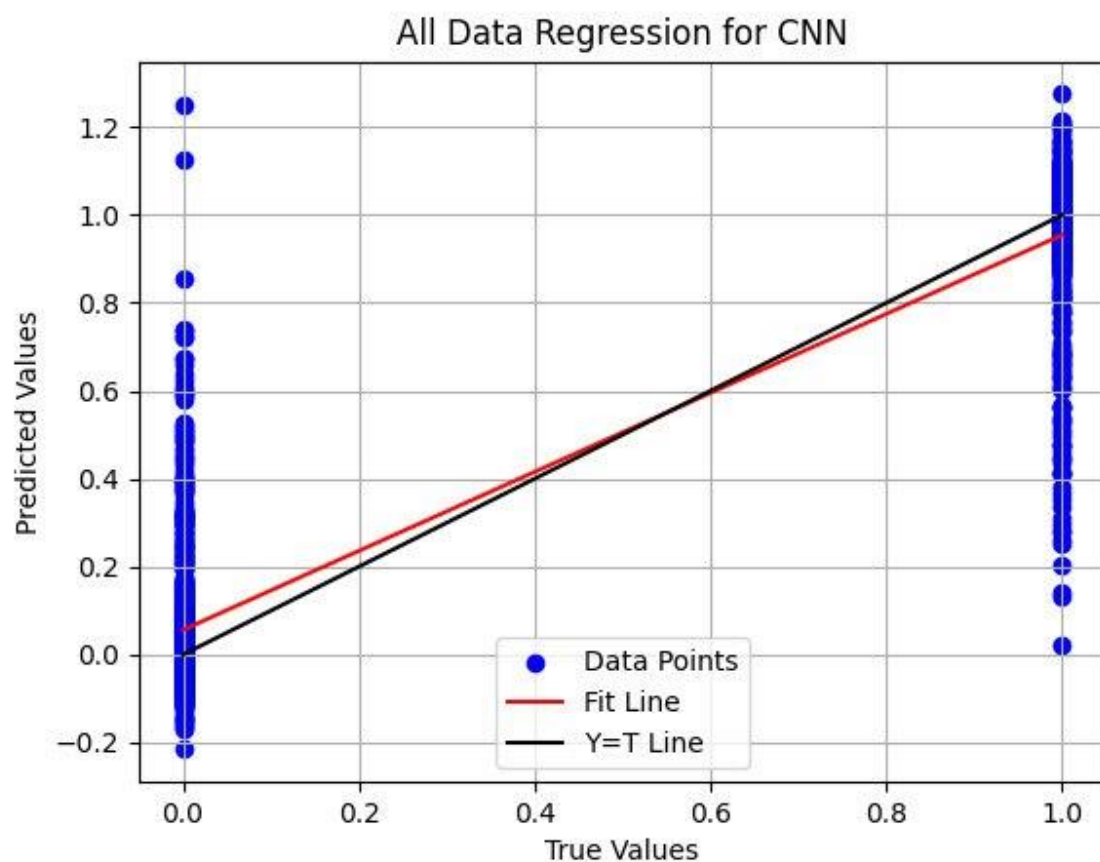
Deep Learning Techniques:

Convolution Neural Network





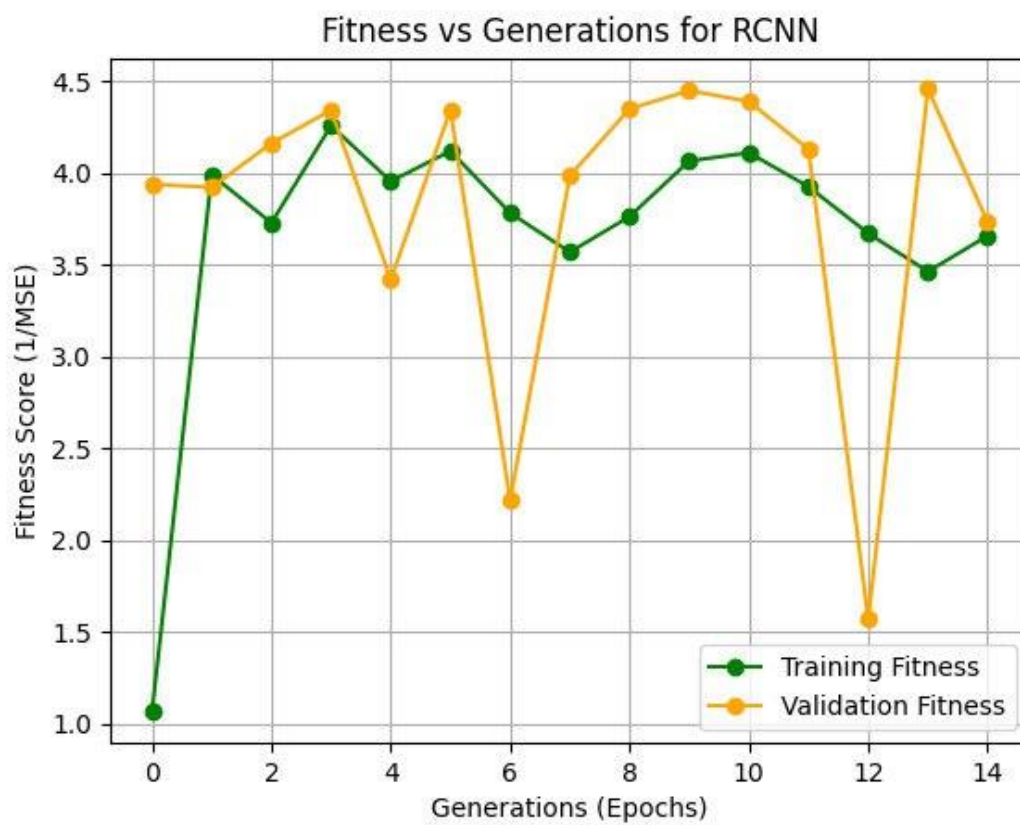
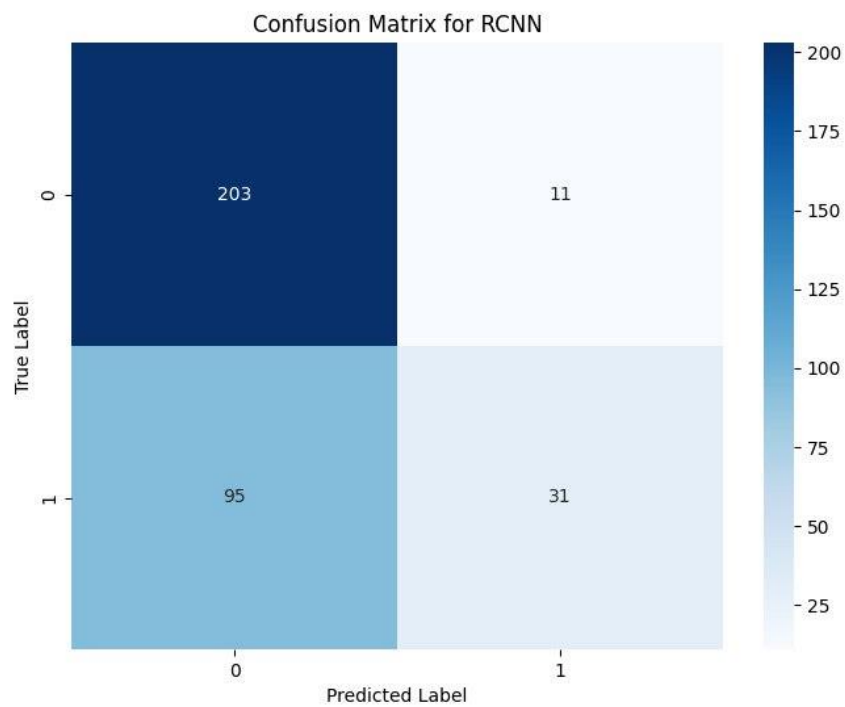


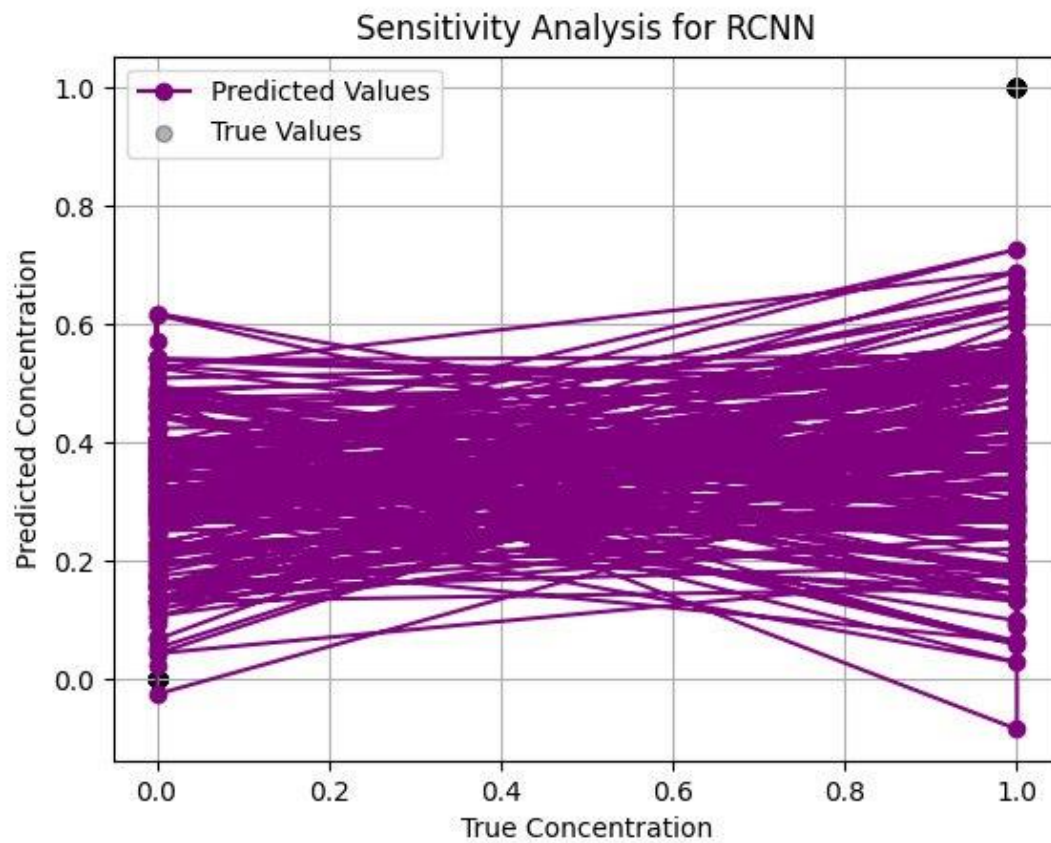
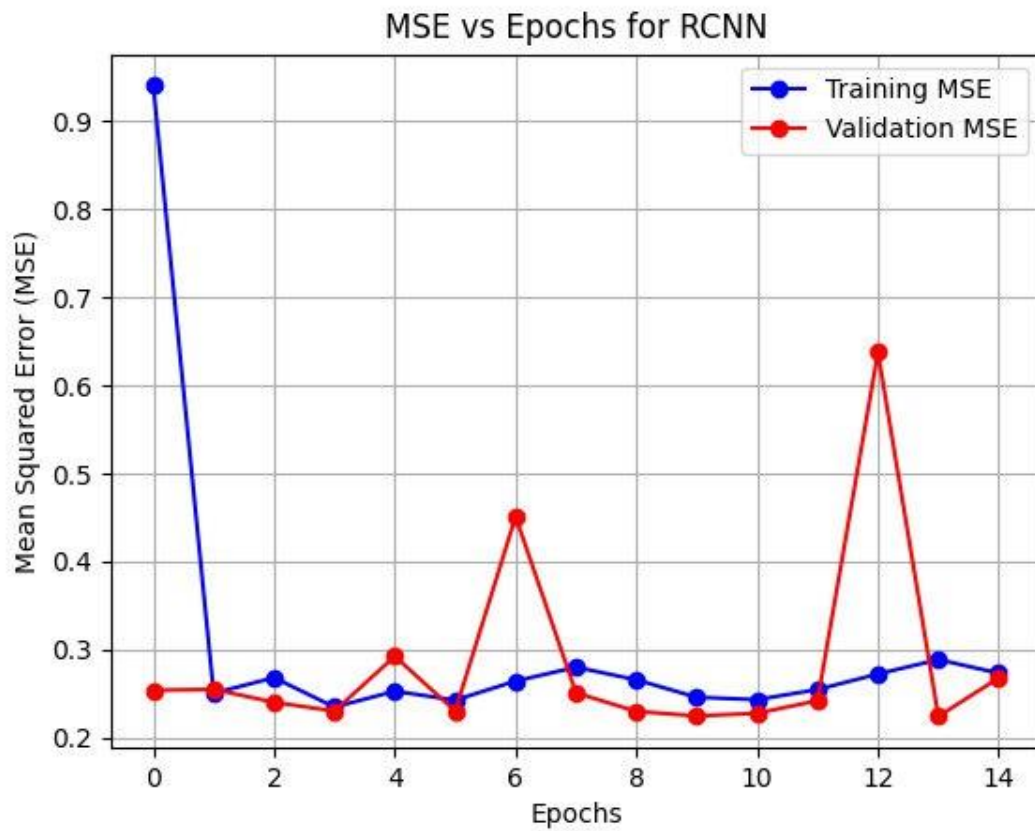


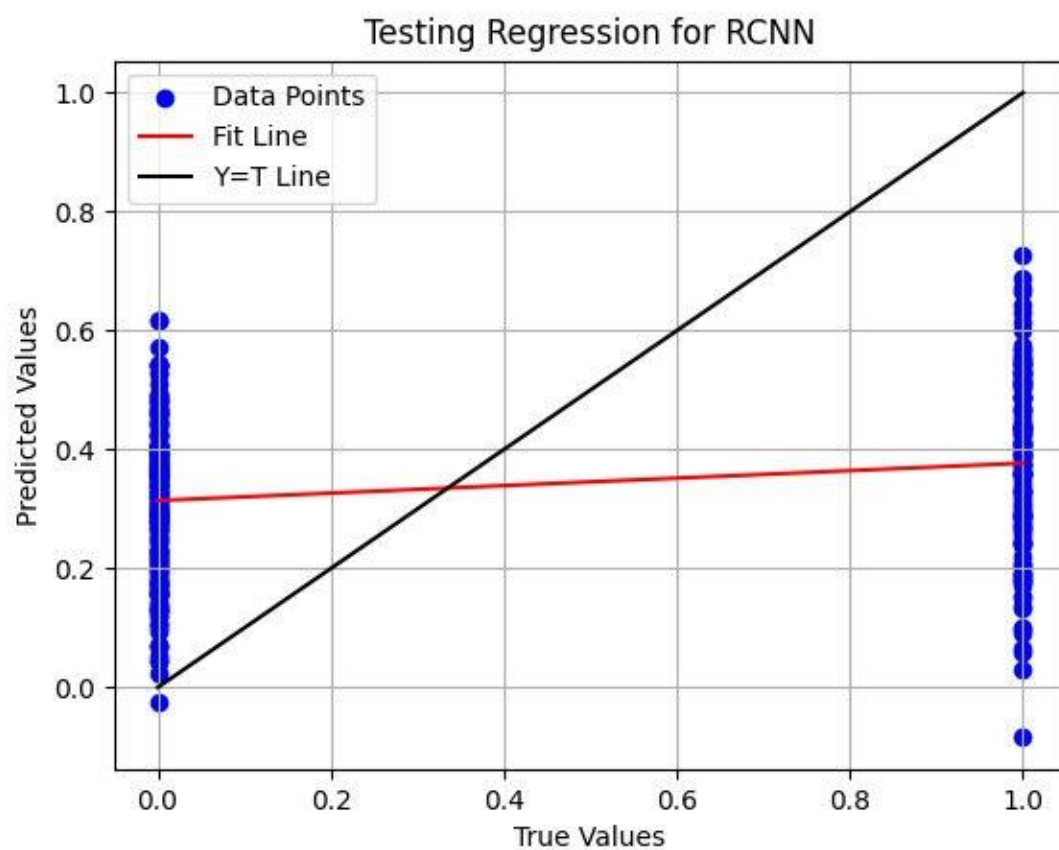
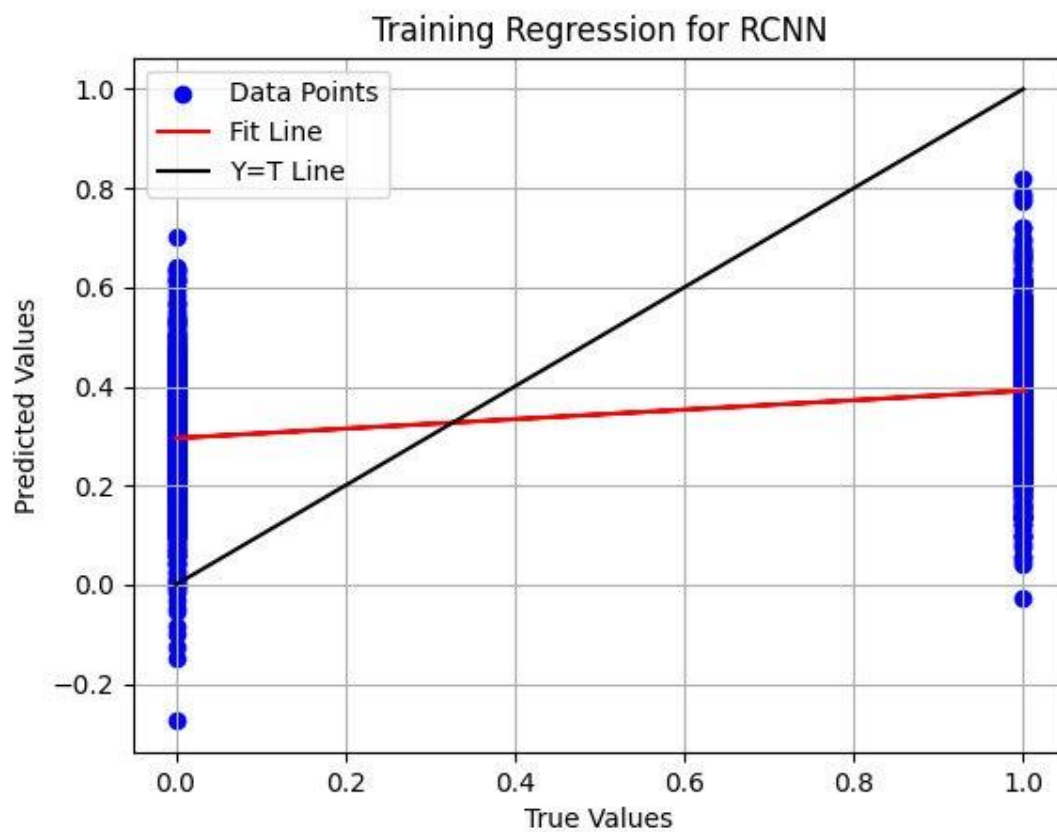
Metric	Score
Accuracy	0.852941176470588
Precision	0.852510717548668
Recall	0.852941176470588
F1 Score	0.852694938440493

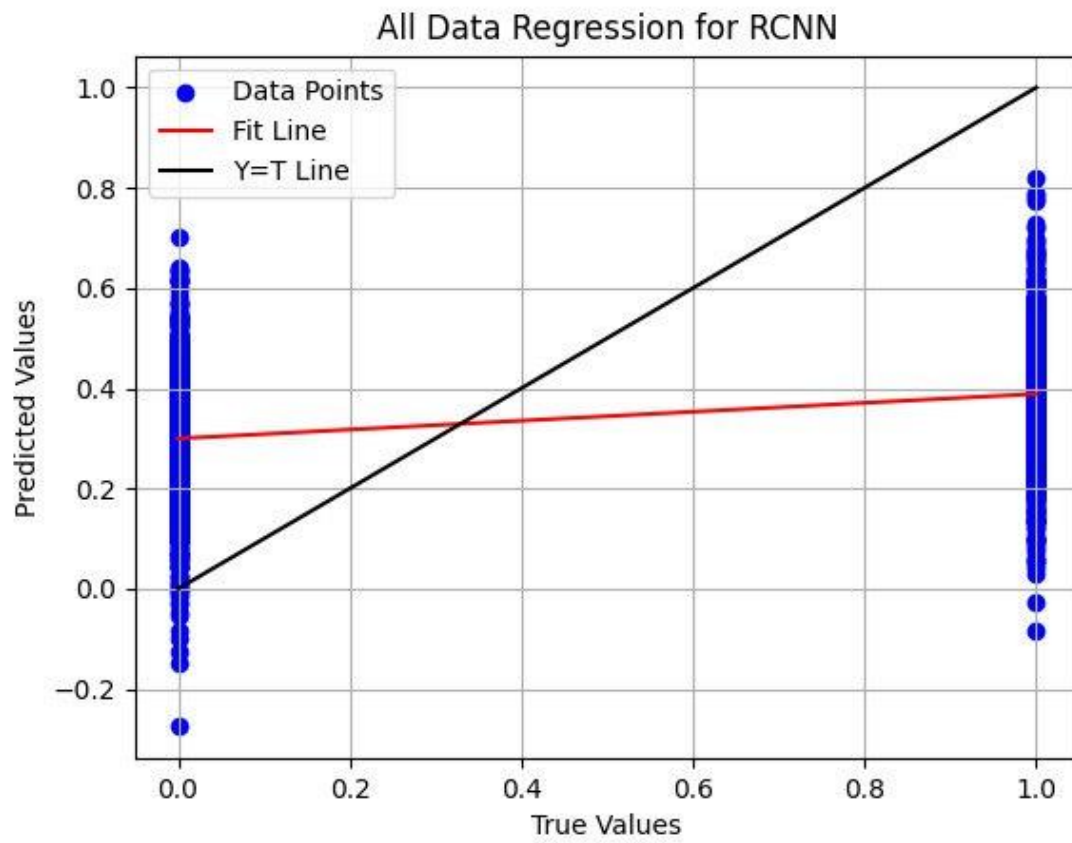
Metric	Train	Test
MSE	0.00312260576918241	0.115480389715828
R2 Score	0.987198531627655	0.504912734031677

Region Based CNN





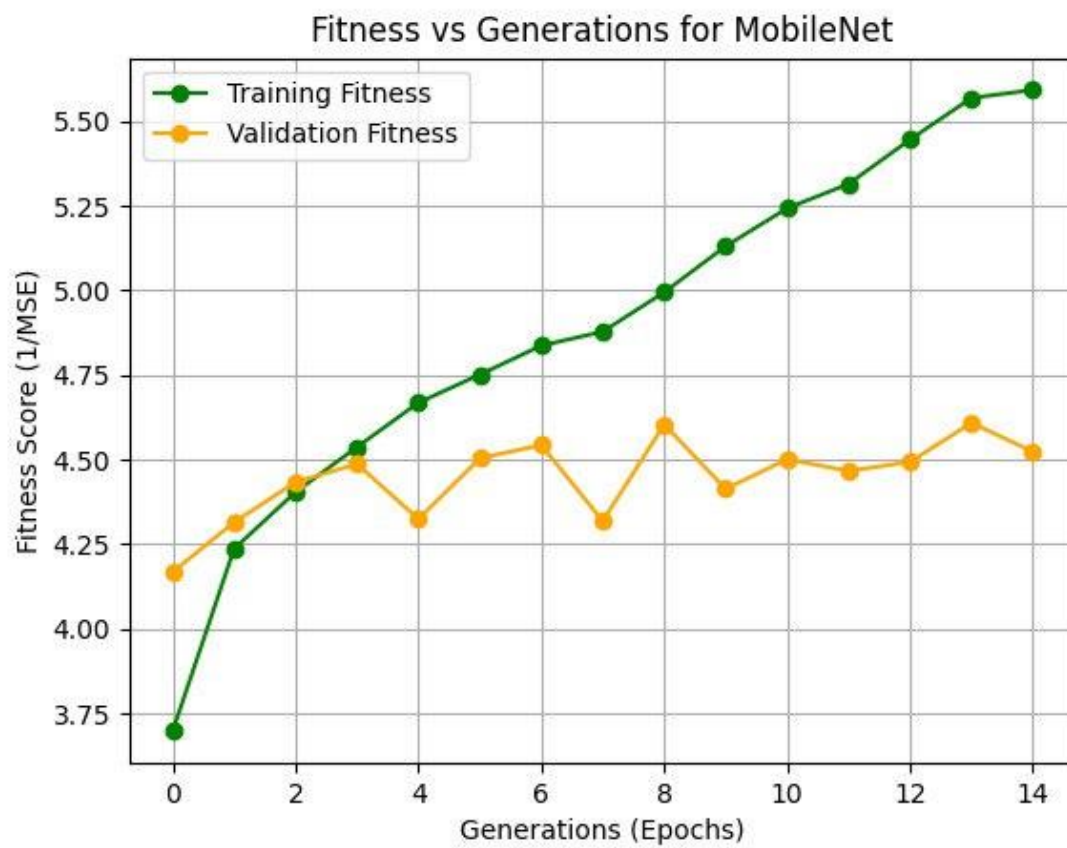
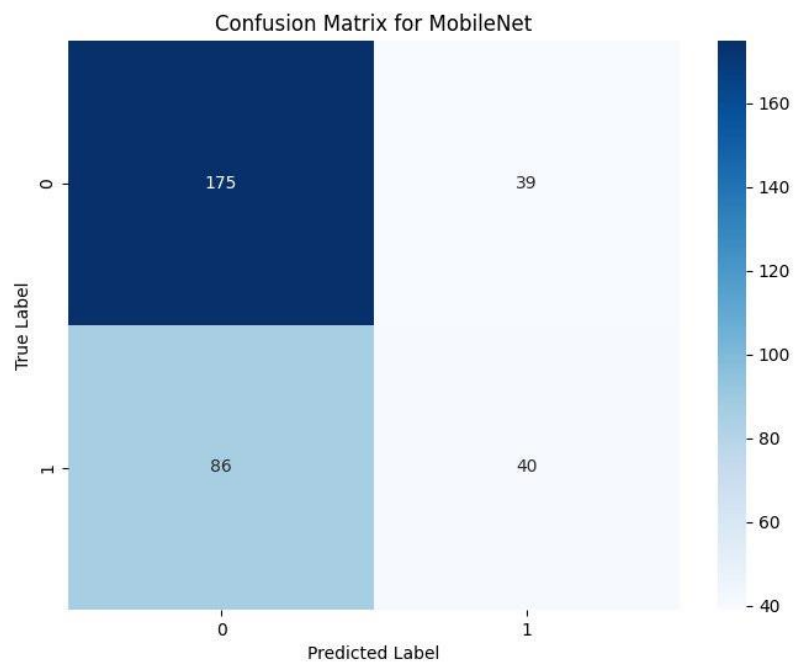


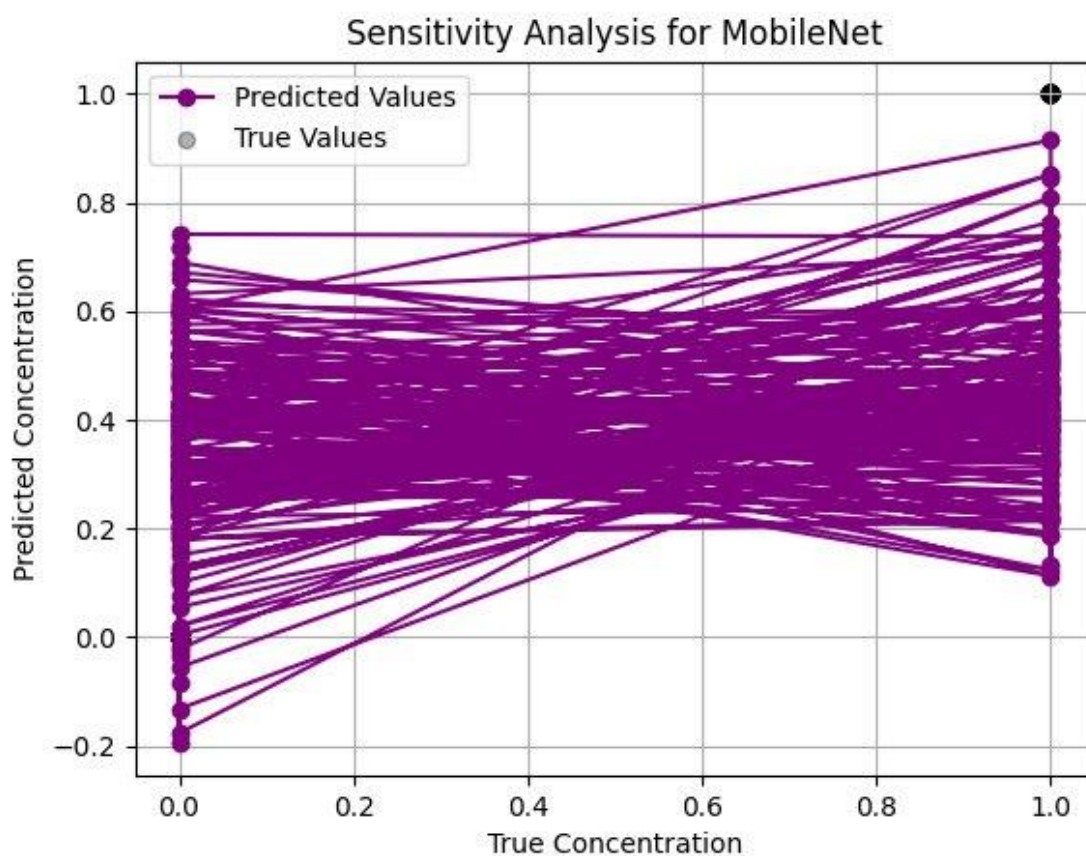
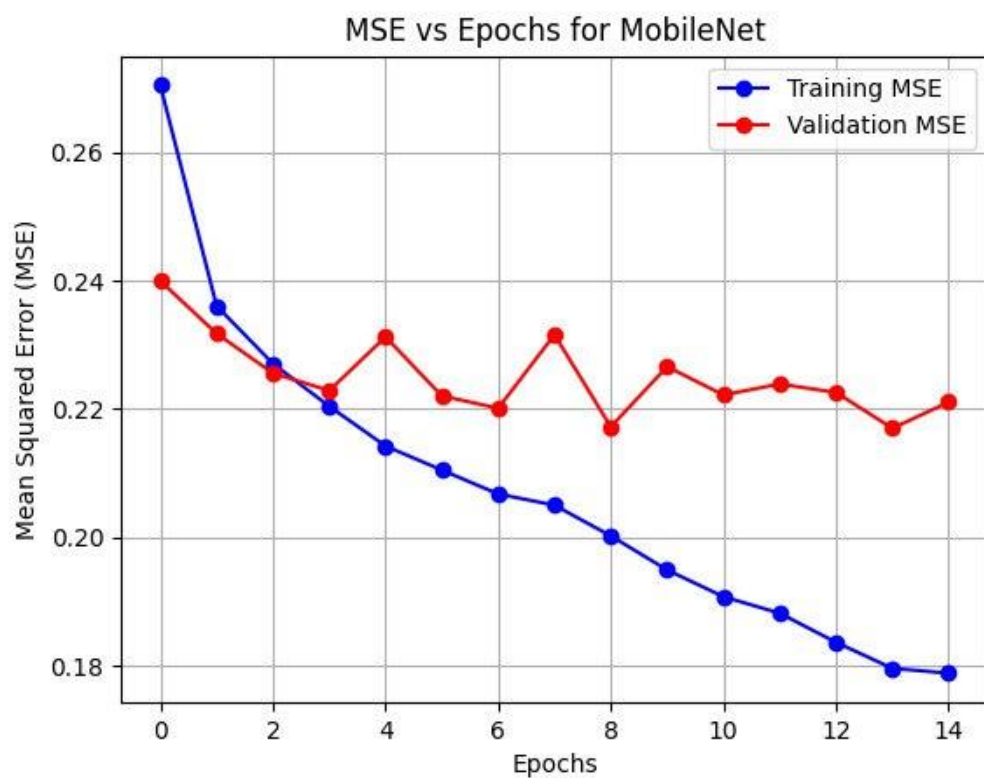


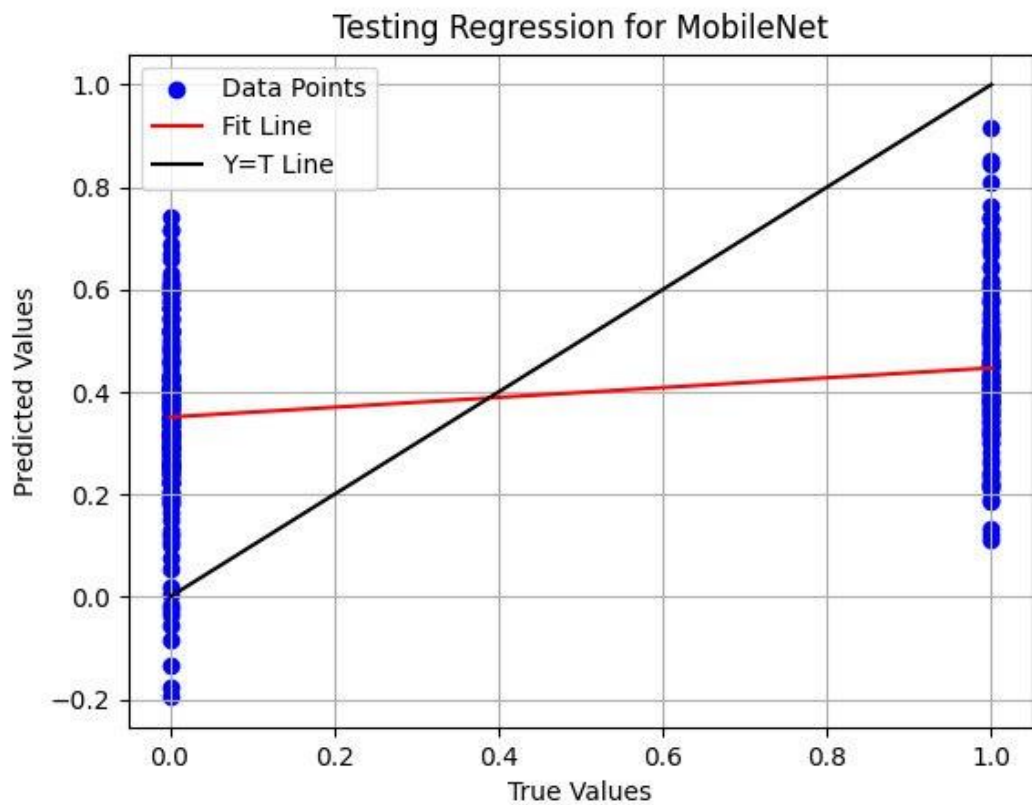
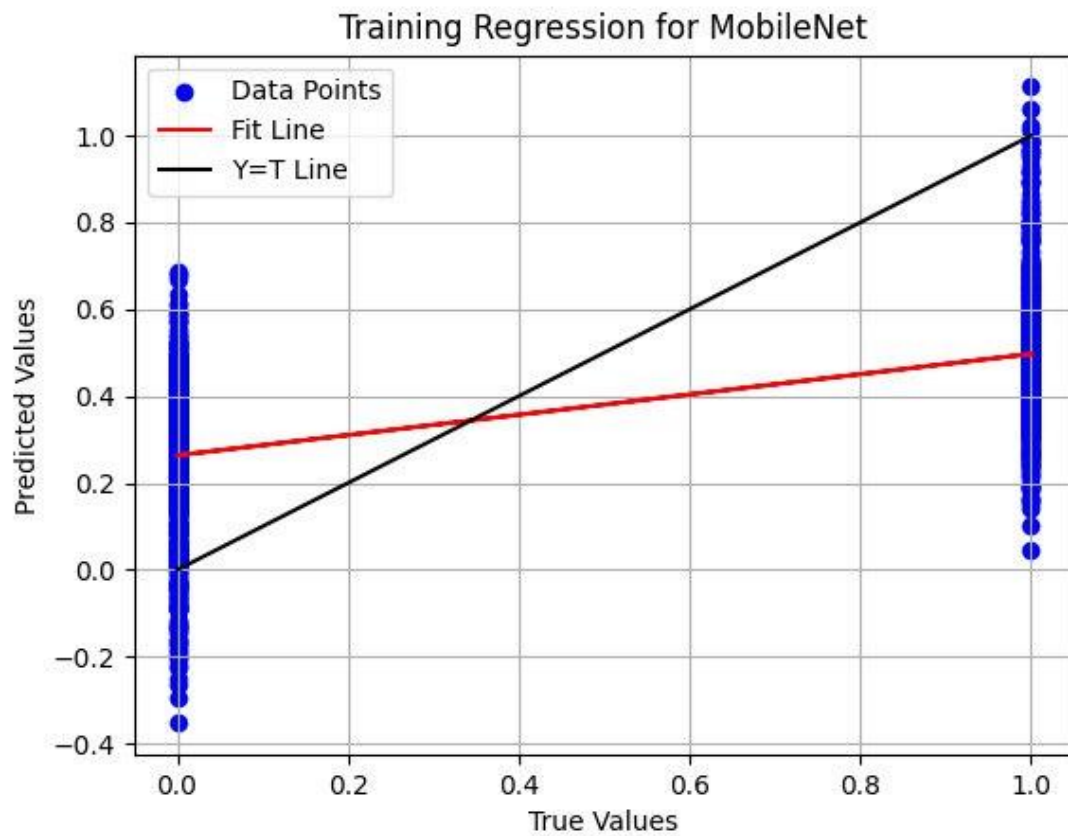
Metric	Score
Accuracy	0.688235294117647
Precision	0.702289774970391
Recall	0.688235294117647
F1 Score	0.635868566176471

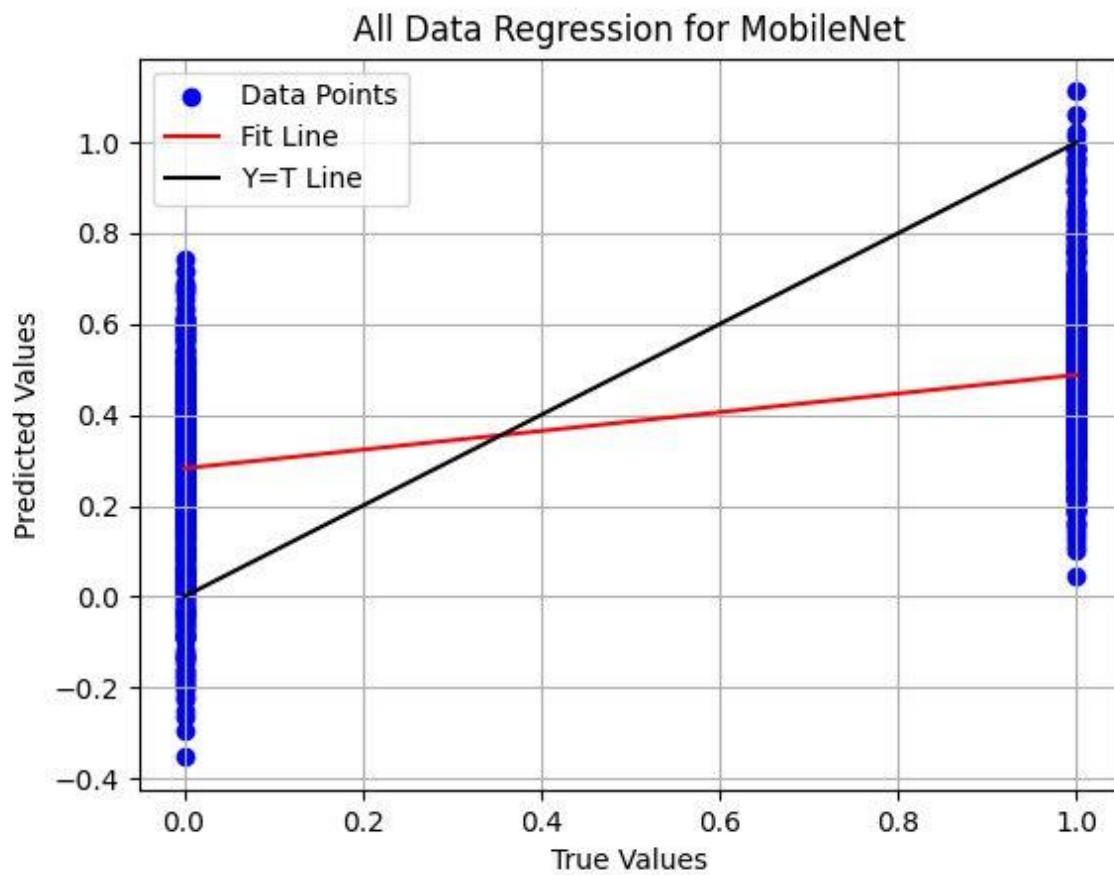
Metric	Train	Test
MSE	0.225199130097909	0.224222622192482
R2 Score	0.0767694711685181	0.0387131571769714

MobileNet





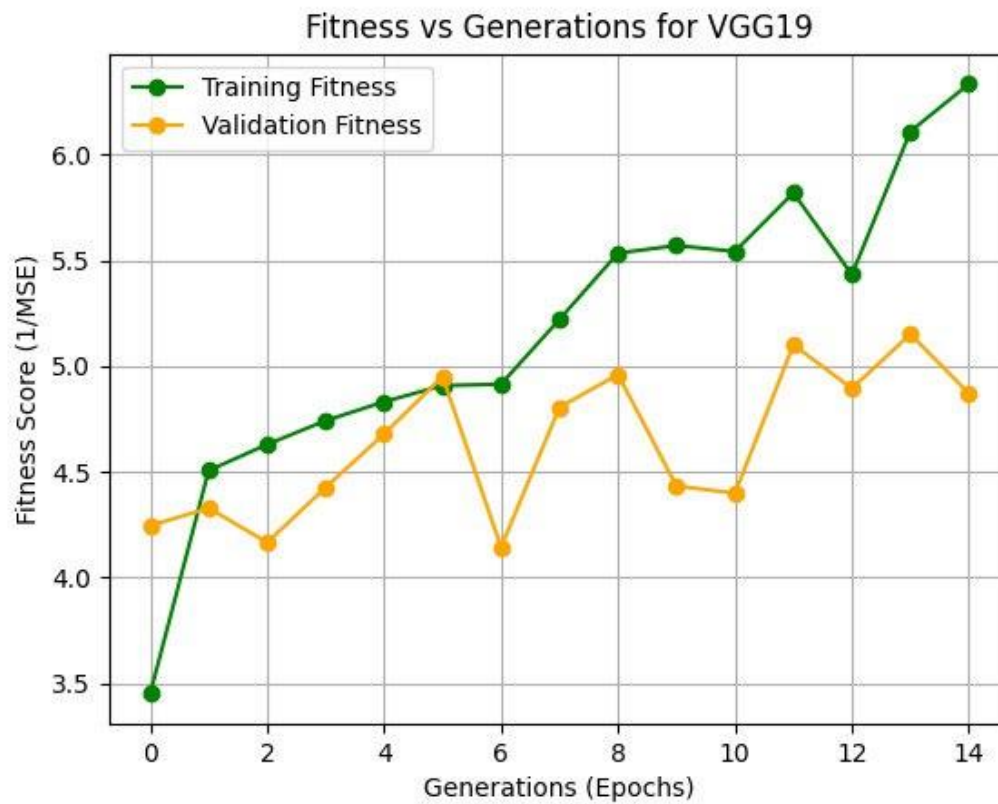
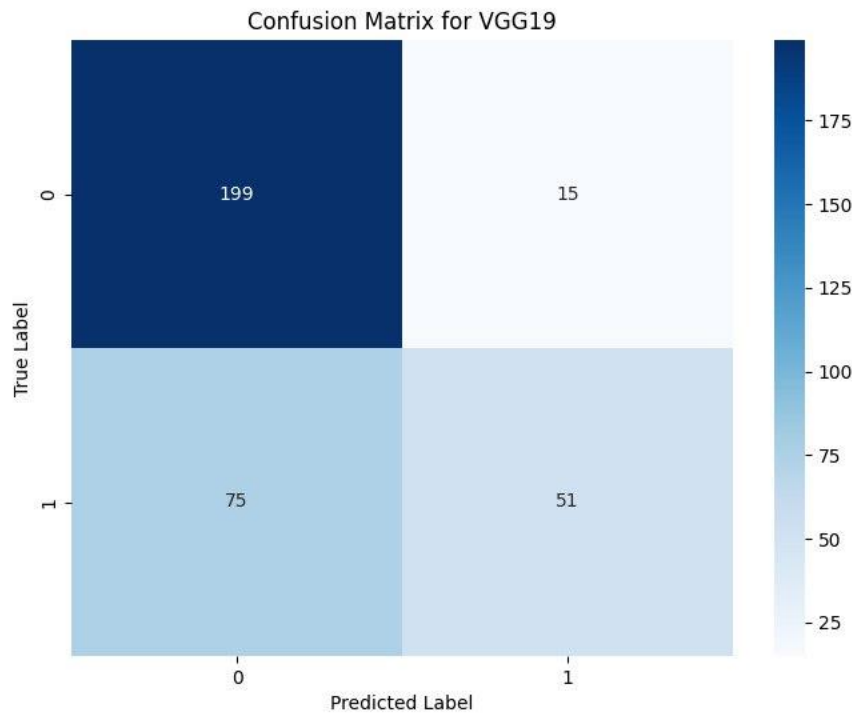


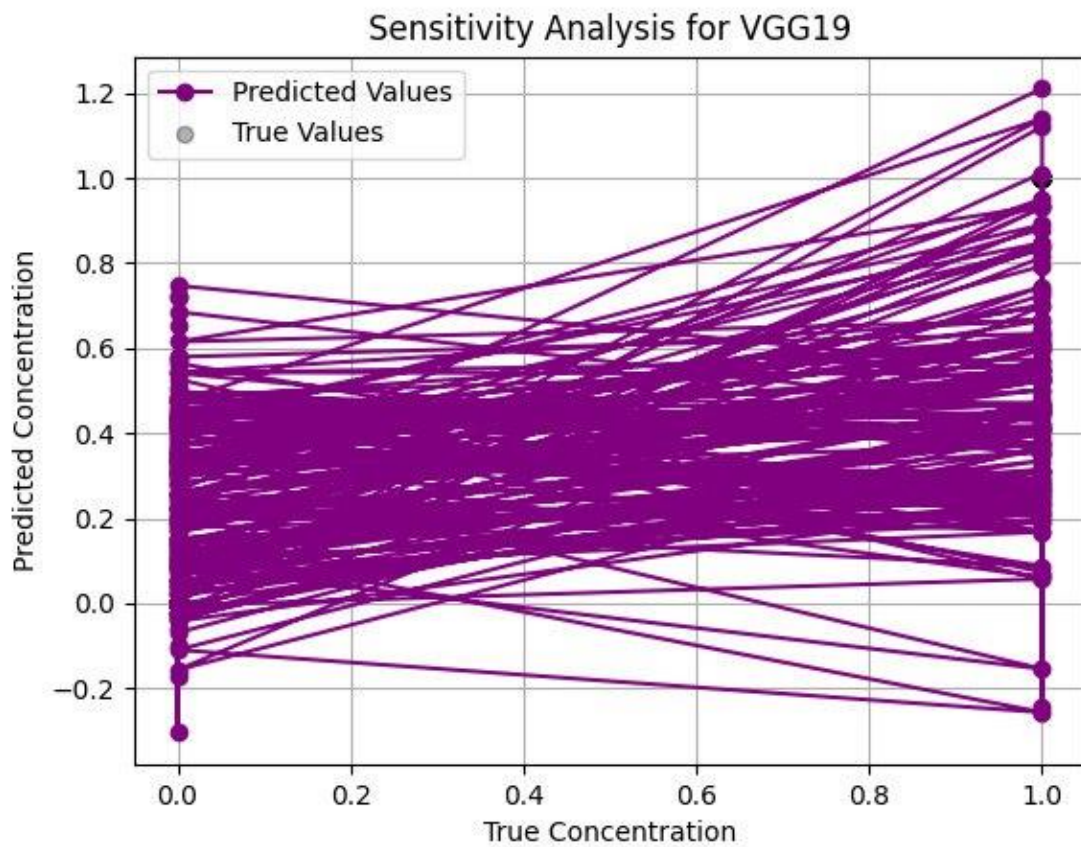
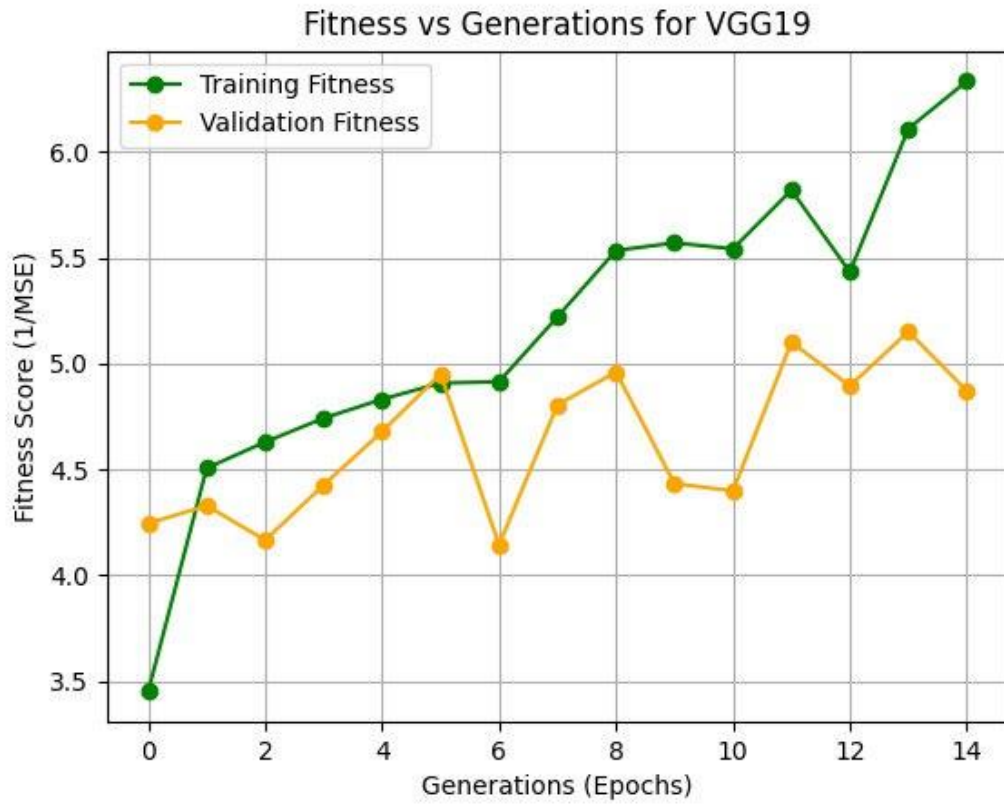


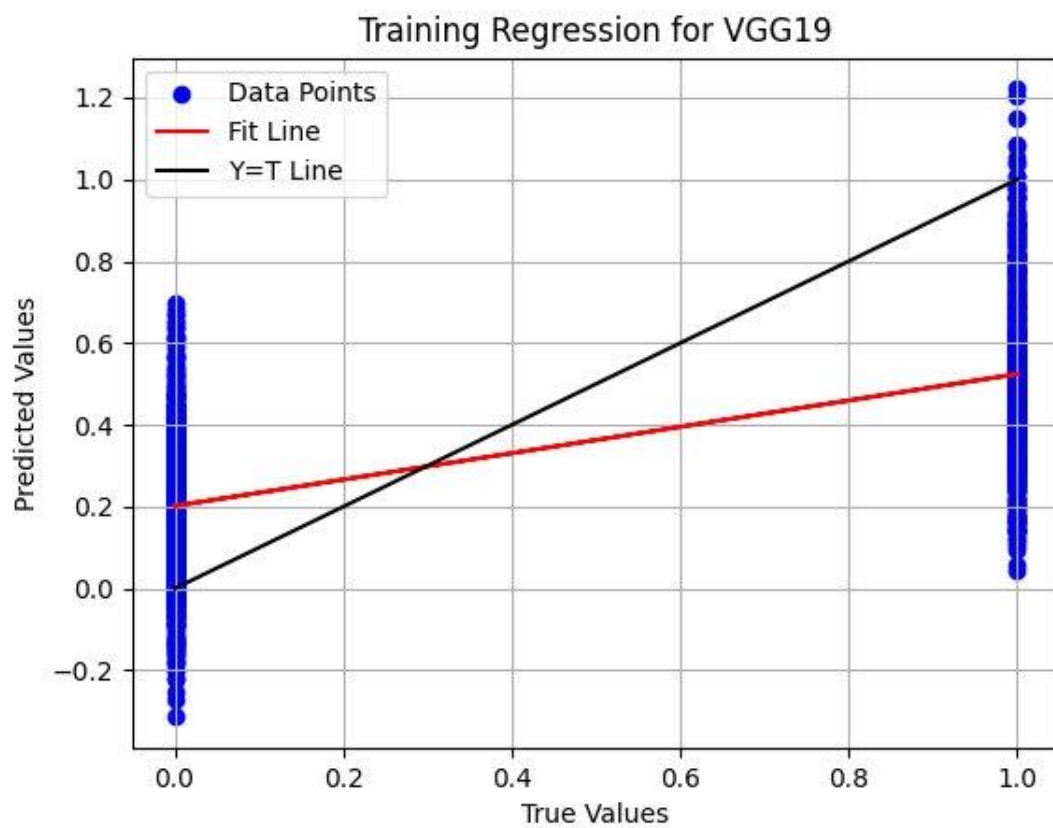
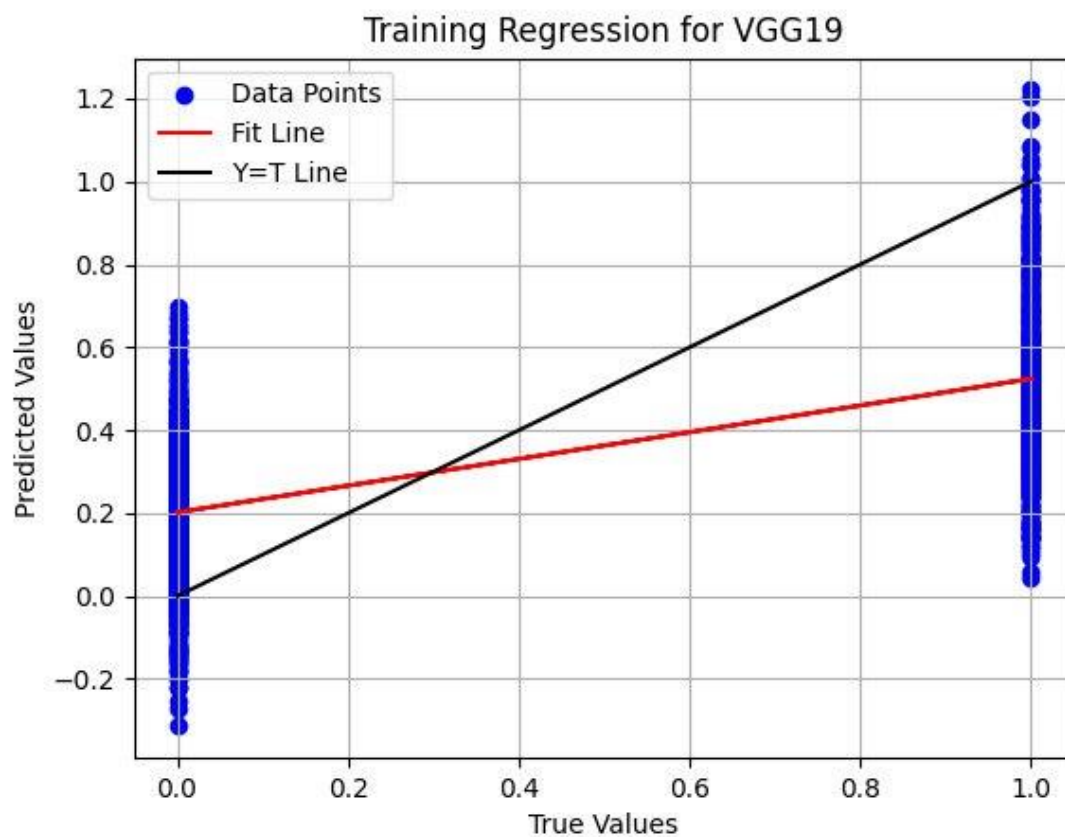
Metric	Score
Accuracy	0.632352941176471
Precision	0.609658995272778
Recall	0.632352941176471
F1 Score	0.60839688892245

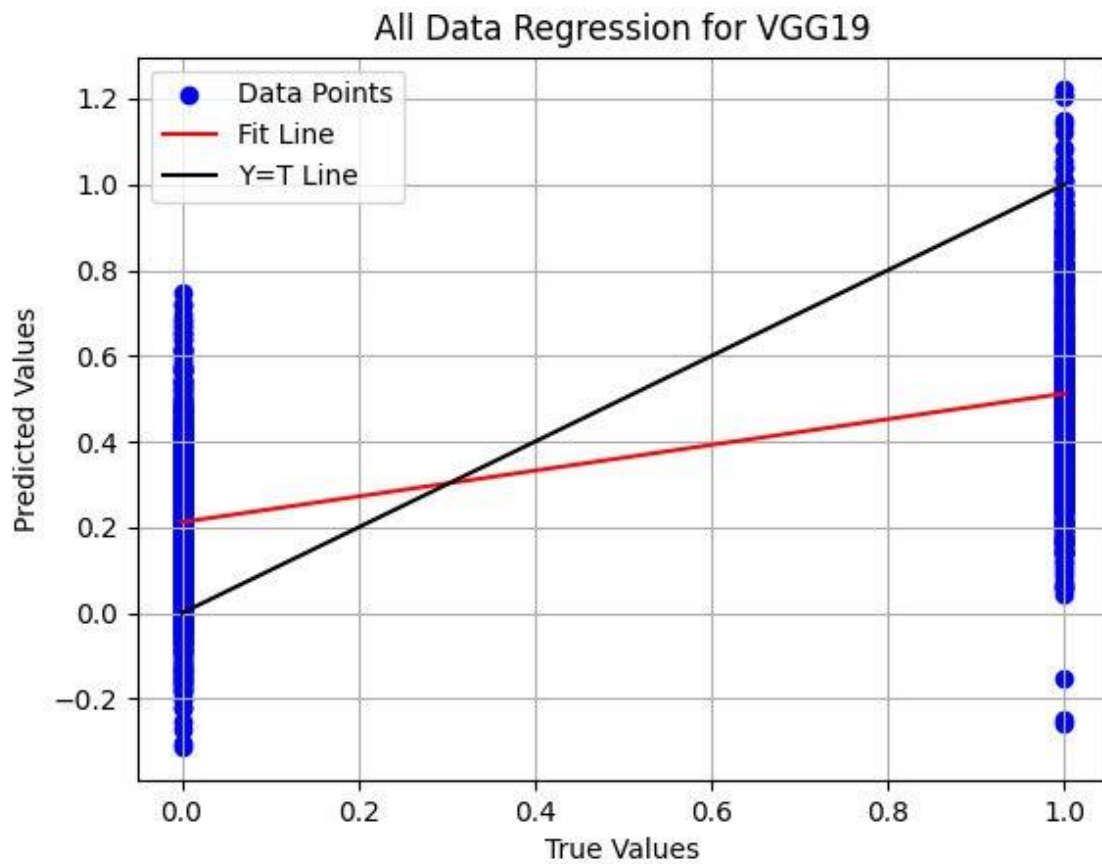
Metric	Train	Test
MSE	0.176252538004267	0.216999596678661
R2 Score	0.277431905269623	0.0696797966957092

VGG19





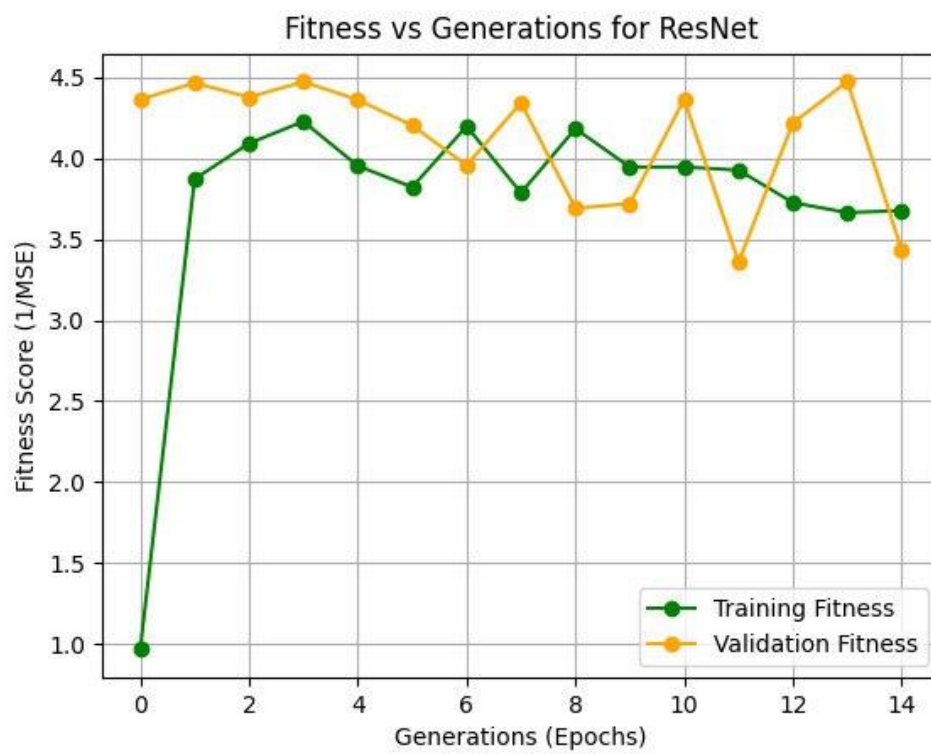
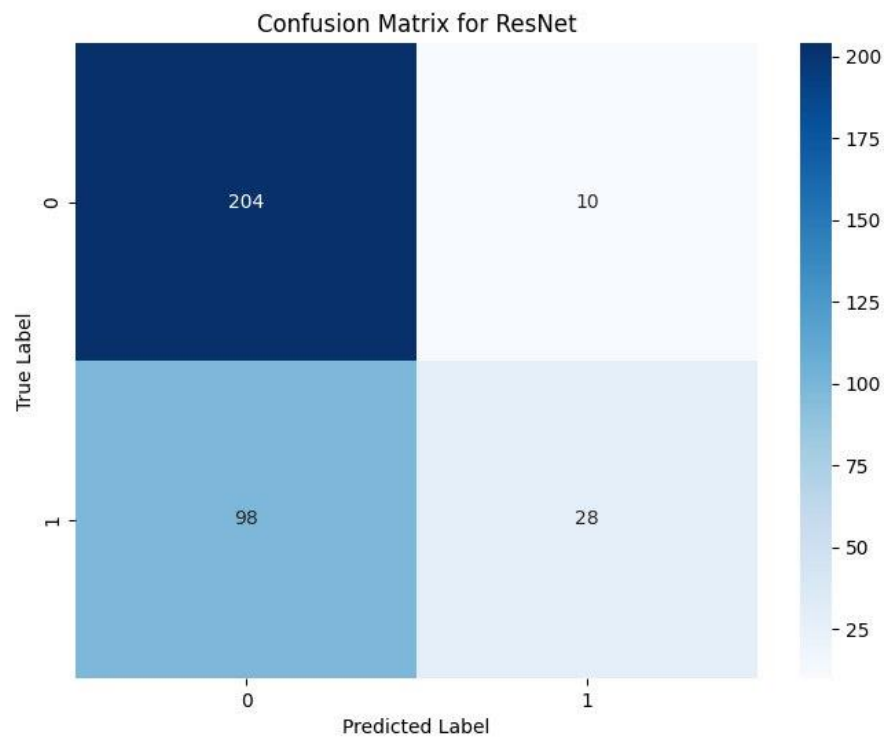


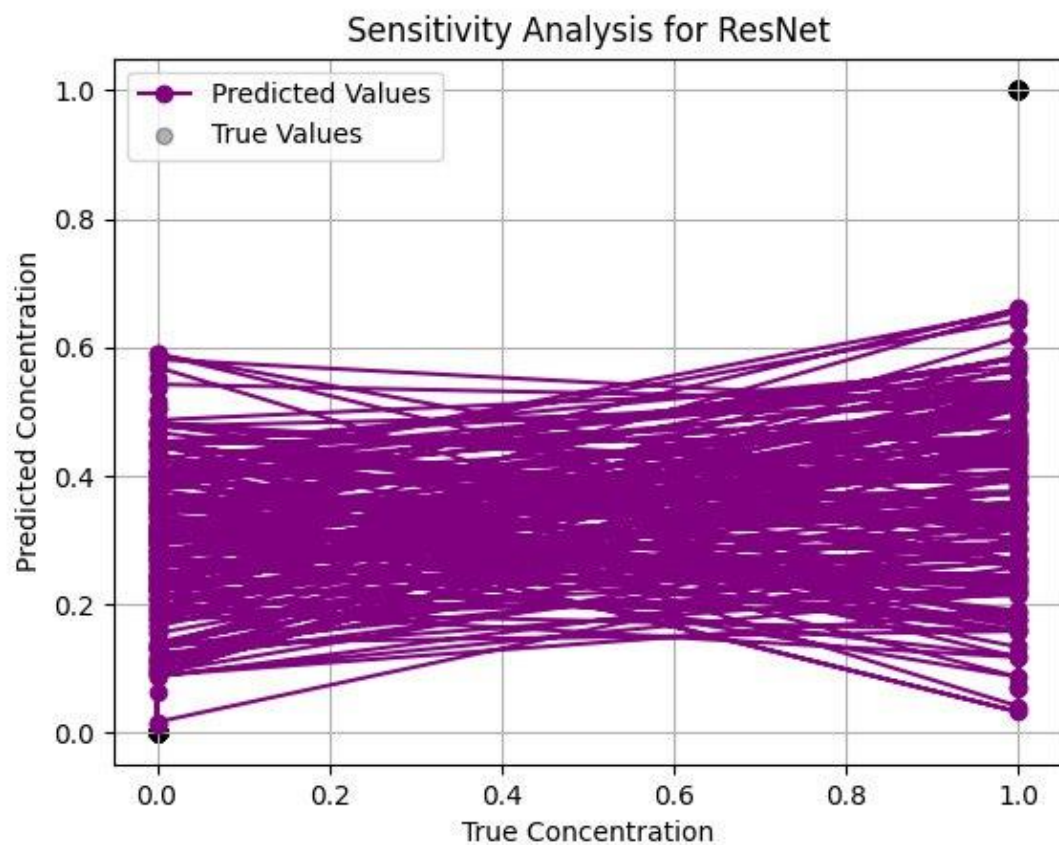
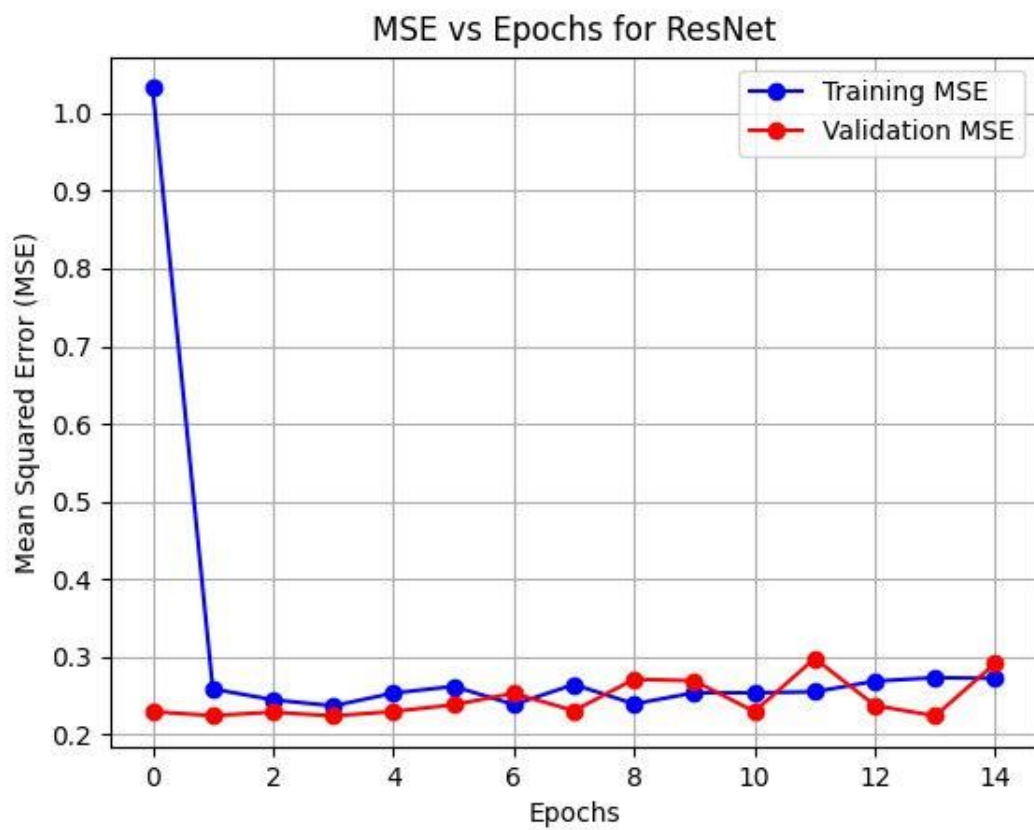


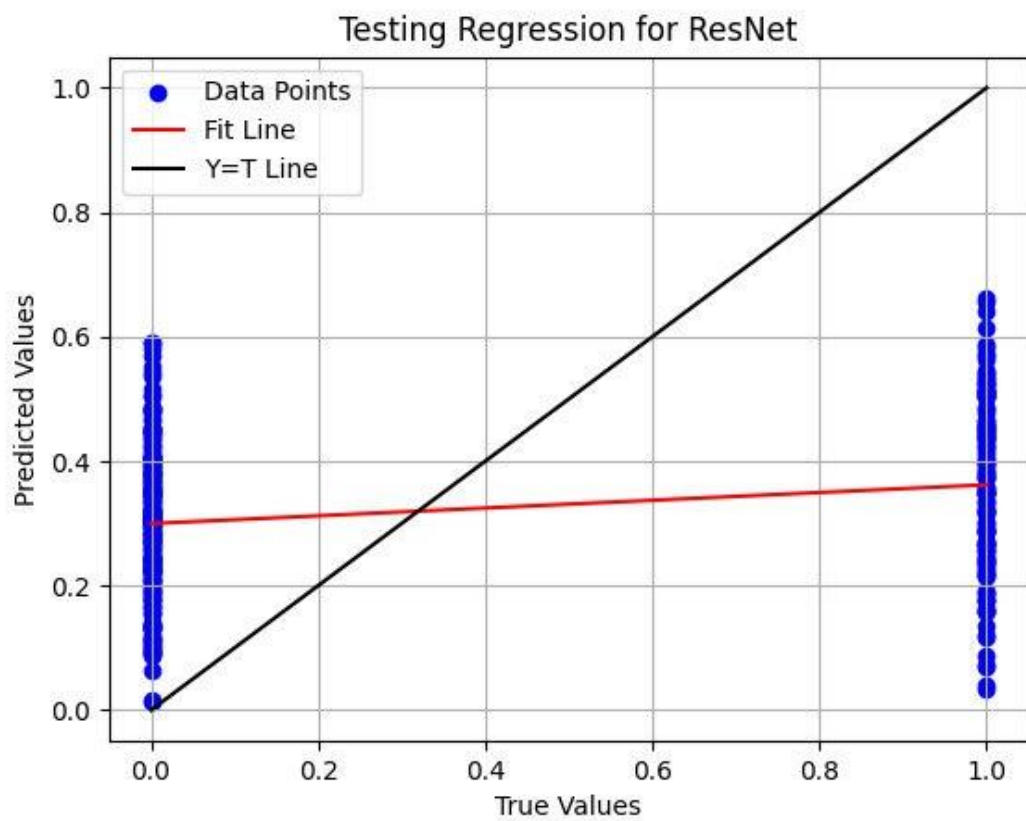
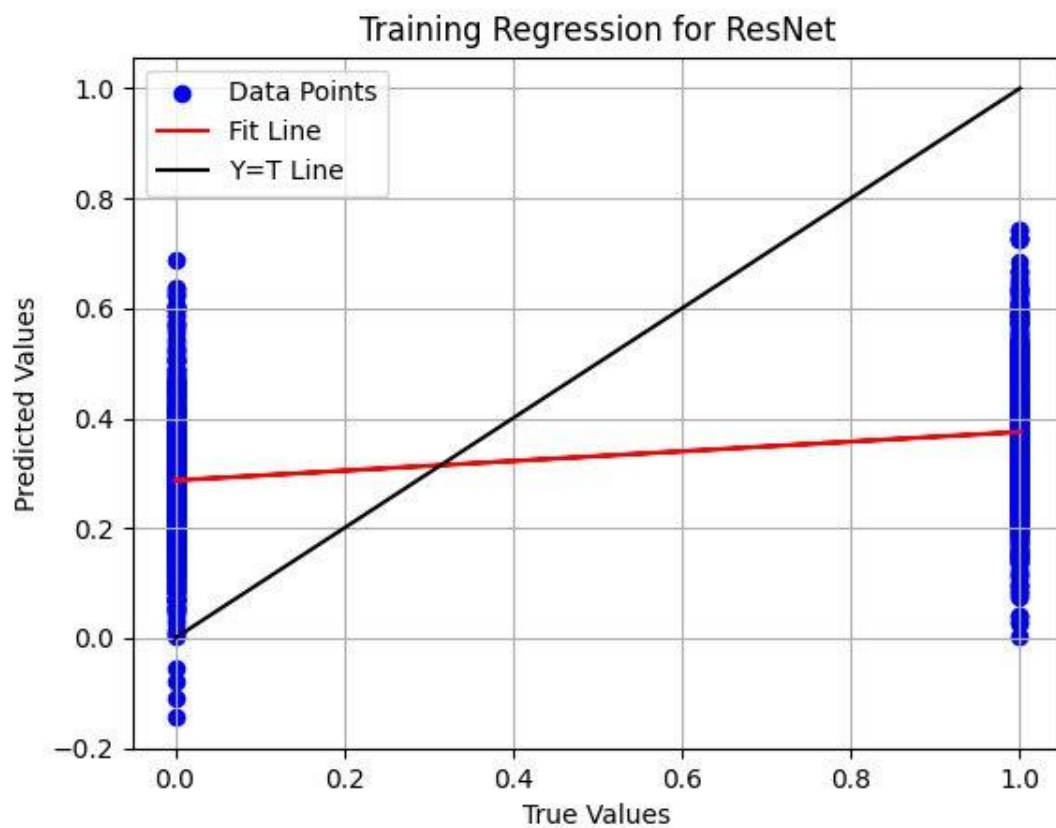
Metric	Score
Accuracy	0.735294117647059
Precision	0.7434911589055
Recall	0.735294117647059
F1 Score	0.710206726133076

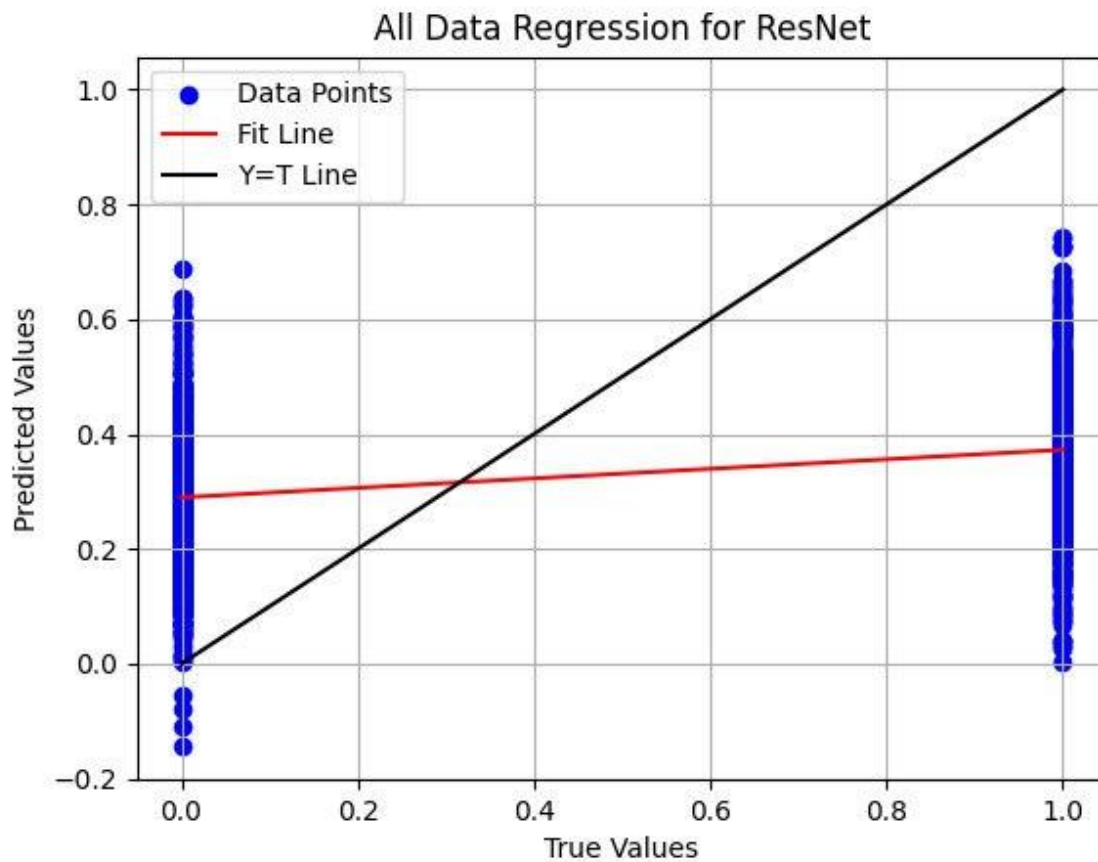
Metric	Train	Test
MSE	0.156536089760672	0.194114256963704
R2 Score	0.35826188325882	0.167793810367584

ResNet50









Metric	Score
Accuracy	0.682352941176471
Precision	0.698230578393783
Recall	0.682352941176471
F1 Score	0.624216742851423

Metric	Train	Test
MSE	0.228988089879994	0.223647188335691
R2 Score	0.0612363219261169	0.0411801934242249

All DL Models

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

Machine Learning VS Deep Learning

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

2.7 Assumptions and Dependencies

Assumptions:

- **Image Quality:** The dataset contains high-quality, labeled medical images that are sufficiently diverse to represent real-world scenarios. Images provided for testing and deployment are similar in quality and format to those used during training.
- **Label Accuracy:** The labels in the dataset (Normal or Stone) are accurate, as model performance depends heavily on correctly labeled training data.
- **Computational Resources:** Adequate computational resources (e.g., GPUs or high-performance CPUs) are available for model training, testing, and real-time predictions.
Consistency in Imaging Techniques: The imaging techniques used for collecting the dataset are consistent, ensuring minimal variation in image features.
- **User Proficiency:** Healthcare professionals using the system have basic proficiency with technology and can operate the interface effectively.
- **Regulatory Compliance:** The dataset complies with all ethical and regulatory requirements for medical image usage and patient confidentiality.

Dependencies:

- **Data Availability:** The success of the project relies on access to a sufficiently large and balanced dataset of labeled kidney images for training and validation.
- **Hardware Infrastructure:** Training and deployment depend on the availability of suitable hardware, such as GPUs for deep learning or servers for real-time inference.
- **Software and Libraries:** The project depends on machine learning libraries like TensorFlow, PyTorch, or Scikit-learn for model development. Compatibility issues or software bugs could affect progress.

- **Image Preprocessing Tools:** Tools for image preprocessing (e.g., resizing, normalization) are essential for preparing the dataset for training.
- **Stakeholder Support:** Collaboration with domain experts, such as radiologists, is necessary to validate the system's outputs and guide improvements.
- **Regulatory Approvals:** If deployed in a clinical setting, the system's use will depend on regulatory approvals for AI-based diagnostic tools.
- **Internet Connectivity:** If the system integrates with cloud-based tools for processing or storage, reliable internet connectivity is required.

By identifying these assumptions and dependencies, the project can address potential risks and plan mitigation strategies to ensure successful development and deployment.

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