International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 09 Issue: 05 | May - 2025 SJIF Rating: 8.586 ISSN: 2582-3930

Online Payment Fraud Detection Using Machine Learning

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Abstract - With the rise of online transactions, payment fraud has become a critical concern. Traditional rule-based systems are no longer effective against advanced fraud tactics. This project uses machine learning algorithms—Logistic Regression, Decision Tree, Random Forest, and Neural Networks—to detect fraud in real time. It addresses the challenge of imbalanced datasets using techniques like SMOTE. Models are evaluated using accuracy, precision, recall, and F1-score, with Random Forest and Neural Networks showing the best results. The system enhances transaction security by accurately identifying suspicious activities, proving the efficiency of machine learning over traditional fraud detection methods.

***Key Words*:** Online Payment,Fraud Detection,Machine Learning,Imbalanced Data,SMOTE,Random Forest

1.INTRODUCTION

Online payment systems have become a vital part of modern commerce, but with this growth comes an increase in fraudulent activities. Traditional fraud detection methods are often inadequate, as fraudsters continuously evolve their tactics. This project aims to develop a machine learning model to detect fraudulent transactions in real-time. By analyzing transaction data and using algorithms like Logistic Regression, Decision Trees, and Neural Networks, the model will classify payments as legitimate or fraudulent. The systemfocuses on minimizing false positives while accurately identifying fraud. Handling imbalanced datasets is a key challenge addressed through oversampling and under sampling. This study aims to improve fraud detection speed and accuracy compared to rule-based methods. Ultimately, the project contributes to securing online payments and reducing financial losses. The report covers background, methodology, results, and conclusions.

1.1 Background

Online payment systems have become integral to modern commerce, enabling people to make transactions quickly and efficiently. However, the rise in digital payments has led to an increase in online fraud, which poses significant risks to users and financial institutions. Fraudulent activities can result in substantial financial losses, damage to the reputation of businesses, and decreased trust in payment systems. Detecting fraudulent transactions at an early stage is crucial to minimizing these risks.

1.2 Problem Statement

Traditional fraud detection systems often rely on rule-based approaches, which are ineffective at detecting new or evolvingfraud patterns. Fraudsters constantly adapt their methods, making it difficult for static systems to identify suspicious activities. This highlights the need for an intelligent and adaptive solution that can detect fraud in real-time and adapt to new fraud techniques.

1.3 Objective of the Study

This study aims to develop a machine learning model capable of detecting fraudulent online payment transactions. The goal is to build a model that can accurately identify fraudulent transactions while minimizing false positives. By leveraging machine learning algorithms such as Logistic Regression, Decision Trees, Random Forest, and Neural Networks, the project seeks to create an automated system that enhances fraud detection capabilities.

1.4 Scope of the Study

The project involves collecting transaction data, preprocessing it, and applying various machine learning algorithms to detect fraudulent behavior. Key challenges, such as imbalanced datasets, are addressed through techniques Like oversampling and under sampling. Model performance is evaluated using metrics such as accuracy, precision, recall, and F1-score to ensure optimal results.

1.5 Significance of the Study

Implementing a machine learning-based fraud detection system can significantly reduce financial losses and improve security in online payment platforms. The system's ability to detect fraud in real-time enhances the overall user experience, ensuring that legitimate transactions are processed without delay. Additionally, the study demonstrates how machine learning can outperform traditional methods in handling dynamic and evolving fraud patterns. the **Methodology**, including the data collection, preprocessing, and machine

learning algorithms used.

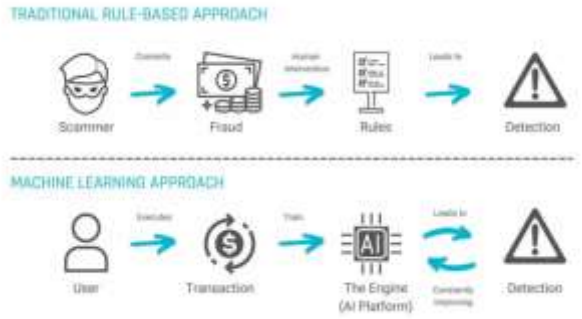

Fig.1.Machine Learning Approach

1.6 Supervised Learning

Supervised Learning is a type of machine learning where a model is trained on labeled data. In this approach, the algorithm learns from input-output pairs, where the input data comes with known output labels.The objective is for the model to learn a mapping from inputs to outputs to predict the correct output for unseen data. Key concepts in supervised learning include:

1. **Labeled Data**: The dataset contains both features (inputs) and corresponding labels (outputs).

2. **Training and Testing**: Data is split into a training set for learning and a testing set for evaluation.

3. **Algorithms**: Common algorithms include Logistic Regression, Decision Trees, Random Forests, Support Vector Machines, and Neural Networks.

4. **Loss Function**: A function used to measure prediction error and guide model training (e.g., Cross-Entropy Loss for classification).

5. **Evaluation Metrics**: Metrics such as accuracy, precision, recall, and F1score are used to evaluate model performance. In **fraud detection**, supervised learning is used to classify transactions as fraudulent or non-fraudulent based on historical data. Features

such as transaction amount, location, and time are used to train the model. The goal is to predict fraud in real-time with high accuracy. Advantages of supervised learning include high accuracy and interpretability, while challenges involve data labelling and potential overfitting.

1.7 Unsupervised Learning

Unsupervised Learning in Fraud Detection focuses on identifying patterns and anomalies in transaction data without requiring labeled fraud data Since fraudulent transactions often deviate from normal behavior, unsupervised learning models can detect these outliers.

How It Works in Fraud Detection:

1. **Anomaly Detection**: Unsupervised learning algorithms identify abnormal transactions that do not match typical user behavior or transaction patterns.

2. **Clustering**: Algorithms like **K-Means** group similar transactions together, making it easier to identify outliers (potential fraud).

3. **Dimensionality Reduction**: Techniques like **PCA** reduce the number of features, helping to isolate fraudulent patterns from a large dataset.

4. **Density-Based Clustering (DBSCAN)**: Identifies clusters of transactions based on density. Fraudulent transactions are often far from normal clusters.

5. **Autoencoders**: Neural networks trained to reconstruct input data can detect unusual transactions by comparing the reconstruction error, with high error indicating potential fraud.

Fig.2.Architecture of Fraud Detection System

1.7.1 Advantages in Fraud Detection:

No Need for Labeled Data: Since fraud detection systems may not have labeled data for training, unsupervised learning doesn't require manually labeled fraud cases.

Adaptability: Models can adapt to new fraud tactics that weren't previously seen in the data.

Real-time Monitoring: These models can detect fraud in real-time, identifying unusual patterns as they emerge.

1.7.2 Challenges:

False Positives: Without labeled data, there's a risk of flagging legitimate

transactions as fraudulent.

Evaluation: It's harder to evaluate the model's accuracy without a ground truth.

Here's the revised methodology section with all instances of section **3** changed to **2**, maintaining the original formatting and content flow:

2.METHODOLOGY

The methodology for detecting fraud in online payment systems using machine learning involves several stages, including data collection, data preprocessing, feature engineering, model selection, training, and evaluation. Below is a detailed breakdown of the approach:

2.1 Data Collection:

The first step in fraud detection is acquiring transaction data. The dataset typically includes information such as transaction amount, timestamp, merchant details, user details, location, and device type. It may also include labels indicating whether a transaction is fraudulent or legitimate. Public datasets like the Kaggle Credit Card Fraud Detection Dataset or proprietary datasets from financial institutions can be used.

Data collection is a foundational step in building machine learning models for online payment fraud detection, as the quality, diversity, and relevance of the data directly affect model performance and reliability. The process typically begins with the acquisition of transactional datasets from financial institutions, online payment gateways, or public repositories such as the IEEE-CIS Fraud Detection dataset or anonymized data from platforms like Kaggle.

These datasets contain detailed records of transactions, including attributes such as transaction amount, timestamp, device and browser information, IP address, geolocation, merchant category, and user identifiers. In industry settings, real-time transaction logs are collected using backend monitoring systems that capture both successful and failed payment attempts, along with metadata related to user behavior, such as login history, purchase frequency, and session duration.

To enhance detection capability, external data sources—such as geolocation databases, device fingerprinting tools, and public threat intelligence feeds—are often integrated to enrich the raw transaction data. Depending on the detection framework, both labeled and unlabeled data may be collected.

In supervised learning, historical transactions are manually or semi-automatically labeled as fraudulent or legitimate based on feedback from fraud analysts, chargebacks, or customer reports. In unsupervised or semi-supervised setups, the focus is on collecting a large volume of unlabeled transactions to model normal behavior and detect outliers.

A key part of the methodology involves data anonymization and privacy preservation to comply with regulations such as GDPR or PCI-DSS, ensuring that personally identifiable information (PII) is either removed or securely encrypted. Furthermore, data collection must consider temporal consistency, as fraud patterns often evolve over time, requiring a representative mix of old and new data to ensure model generalizability. Another important consideration is the balancing of classes, since real-world datasets are highly imbalanced. To address this, techniques like synthetic oversampling (e.g., SMOTE), downsampling of majority classes, or careful selection of balanced time windows may be applied during or after the collection process.

In summary, the data collection methodology for online payment fraud detection is a multi-stage, iterative process that emphasizes the gathering of high-quality, diverse, and ethically sourced data. It integrates raw transaction logs with enriched contextual information and ensures data security and compliance, ultimately providing a robust foundation for training, testing, and validating machine learning models in real-world fraud detection systems.

2.2 Data Preprocessing:

Data preprocessing is a crucial step in preparing raw transaction data for machine learning models in online payment fraud detection. Given the complex and often noisy nature of financial datasets, effective preprocessing ensures that the input data is clean, consistent, and suitable for model training, ultimately improving accuracy and reducing errors.

The first stage typically involves data cleaning, where missing values are handled—either by imputation, deletion, or using default values—depending on the context and importance of the missing features. Duplicate entries, which may arise due to system logging errors or repeated transactions, are also removed to prevent model bias.

Next, data normalization or standardization is applied to ensure numerical features like transaction amount or account balance are on the same scale, which is especially important for algorithms sensitive to feature magnitude, such as SVM or KNN. Categorical variables, such as transaction type, device used, or location, are transformed into numerical form using encoding techniques like one-hot encoding or label encoding.

For time-based features, such as transaction timestamps, new variables can be derived (e.g., hour of the day, day of the week, time since last transaction) to uncover temporal patterns linked to fraudulent behavior.

Feature selection and dimensionality reduction methods, such as correlation analysis, mutual information, or Principal Component Analysis (PCA), are used to eliminate irrelevant or redundant features that can introduce noise and reduce model performance.

Handling imbalanced data is another critical step, as fraudulent transactions are significantly fewer than legitimate ones. Techniques such as SMOTE (Synthetic Minority Over-sampling Technique), random oversampling, undersampling, or cost-sensitive learning help ensure that the model does not ignore minority fraud cases.

Lastly, data splitting into training, validation, and test sets ensures that models are evaluated on unseen data to prevent overfitting. In real-time detection systems, preprocessing pipelines are often automated to transform incoming data streams in real time, ensuring consistent model input. Overall, thorough and context-aware data preprocessing creates a robust foundation for building accurate, scalable, and responsive fraud detection models.

• Handling Missing Values:
Any missing or incomplete data is imputed or removed.
• Feature Scaling:
Features like transaction amounts may need to be scaled using techniques like Min-Max Scaling or Standardization to ensure they are within a similar range.
• Data Balancing:

2.3 Feature Engineering:

Feature engineering plays a pivotal role in enhancing the performance of machine learning models in online payment fraud detection by transforming raw transaction data into informative, discriminative, and predictive features. Since fraudulent behavior often hides within subtle and complex patterns, well-crafted features can significantly improve the model's ability to distinguish between legitimate and fraudulent transactions.

The process typically begins by deriving statistical features, such as the mean, standard deviation, and frequency of transactions over various time windows (e.g., last hour, day, or week), which help capture abnormal activity like sudden spending spikes or unusually frequent transactions.

Temporal features are also critical and include the hour of the transaction, day of the week, time since the last transaction, or velocity of transactions across different merchants and devices. These help identify suspicious timing behaviors, such as purchases made at odd hours or rapid transaction bursts.

Behavioral features reflect individual user habits, such as preferred transaction amounts, merchant categories, or payment methods. Deviations from these habits—like a user suddenly buying from a foreign country—can signal fraud.

Geolocation features and IP address patterns can highlight risky activity, especially if a user transacts from geographically distant locations within short time frames. Similarly, device fingerprinting and browser metadata (e.g., OS, device type, browser version) can be turned into features that track whether a user is transacting from a known or unknown environment. Categorical variables such as merchant ID or payment channel are typically encoded using techniques like one-hot encoding or embedding layers in deep learning models to preserve relational information.

Advanced techniques include aggregated features, such as the number of failed login attempts or total amount spent in the past 24 hours, and cross-feature interactions, where combinations of features (e.g., transaction type + merchant + country) may expose fraud signals not visible in individual features. In some cases, unsupervised feature learning using autoencoders or clustering can generate features that capture latent patterns.

Ultimately, feature engineering in fraud detection is a domain-specific, iterative process requiring deep understanding of both financial systems and adversarial behavior. When effectively executed, it enables machine learning models to uncover hidden signals and improve detection accuracy, reduce false positives, and adapt to new fraud techniques over time.

Feature engineering involves creating new features or modifying existing ones to improve model performance. In fraud detection:

• Transaction Frequency:
The number of transactions made in a short period can be an important indicator of fraud.
• Transaction Location:
Unusual geographic locations or inconsistent location patterns may signal fraudulent activity.
• Behavioral Patterns:
Features such as average transaction amount, time of day, and device usage history are added to enrich the dataset.

2.4 Model Selection:

Various machine learning algorithms are chosen for the task of fraud detection:

• Supervised Learning: Algorithms like Logistic Regression, Random Forest, and Support Vector Machines (SVM) are used for binary classification (fraud vs. non-fraud).
• Unsupervised Learning:
K-Means Clustering, DBSCAN, or Autoencoders can be used to detect anomalies without labeled data.
• Ensemble Methods: Combining multiple models using Random Forest or XGBoost can increase accuracy and reduce overfitting.

2.5 Model Training:

Once the features are selected and data is preprocessed, the model is trained on the dataset. The training process involves feeding the data into the model, adjusting parameters, and optimizing the algorithm to minimize error. Cross-validation is used to avoid overfitting and ensure that the model generalizes well to new, unseen data.

2.6 Model Evaluation:

After training, the model is evaluated using various metrics:

• Accuracy: The proportion of correctly classified transactions.
• Precision: The percentage of actual fraudulent transactions among those predicted as fraudulent.
• Recall: The percentage of actual fraudulent transactions identified by the model.
• F1-Score: The harmonic mean of precision and recall, providing a balanced evaluation of model performance, especially in imbalanced datasets.
• AUC-ROC: The Area Under the Receiver Operating Characteristic curve is used to evaluate classification performance across different thresholds.

2.7 Model Tuning and Optimization:

Hyperparameters of the chosen model are tuned using techniques like Grid Search or Random Search to improve the model's performance. This involves adjusting parameters like learning rate, regularization strength, or the number of trees in a random forest.

2.8 Deployment:

Once the model is trained and optimized, it can be deployed into a real-time fraud detection system. The model will monitor incoming transactions and flag suspicious activities for further investigation. Continuous monitoring and periodic retraining of the model are necessary to keep up with evolving fraud tactics.

2.9 Disadvantages

• Data Imbalance: Fraudulent transactions are much less frequent than legitimate ones, leading to imbalanced datasets. This can cause models to be biased toward predicting legitimate transactions, resulting in poor detection of fraud.
• High Computational Cost: Machine learning algorithms, especially deep learning models, require significant computational resources for training. This can be expensive, especially when processing large transaction datasets in real-time.
• Overfitting: Machine learning models, especially complex ones like neural networks, can overfit the training data, meaning they perform well on historical data but fail to generalize to new, unseen data.

• Lack of Interpretability: Some machine learning models, like deep neural networks, are considered "black-box" models. This makes it difficult to understand how they make predictions, which is a significant issue in industries that require model transparency for compliance or trust reasons.
• Evolving Fraud Tactics: Fraudsters continuously adapt their methods to evade detection. Machine learning models must be constantly retrained with new data to keep up, and there is a risk that the model may miss novel fraud patterns.

2.10 Proposed System:
The proposed system for Online Payment Fraud Detection uses a combination of supervised and unsupervised machine learning algorithms to identify and prevent fraudulent transactions in real-time. The system collects transaction data, processes it through feature engineering, and applies models such as Logistic Regression, Random Forest, and Support Vector Machines (SVM) for supervised classification, while K-Means clustering, DBSCAN, and Autoencoders are employed for anomaly detection in the absence of labeled fraud data. The model is continuously trained using updated transaction data and fine-tuned for optimal performance, minimizing false positives and adapting to emerging fraud patterns. In real-time, the system flags suspicious transactions, which are then reviewed by security teams. With a feedback loop for retraining and a user-friendly dashboard for monitoring, the system ensures adaptive, scalable, and efficient fraud detection while improving overall security and user trust in online payment systems.

2.10.1 Advantages of Proposed System:
• Improved Accuracy: Machine learning models, especially ensemble methods, provide high accuracy in detecting fraudulent transactions by learning complex...

3. MODULES USED

3.1 Data Collection
Data collection is the first and most critical step in any machine learning project, including online payment fraud detection. It involves gathering raw data that will be used to train the machine learning models. For fraud detection, this data typically includes a variety of transaction-related information, such as

- **Transaction ID**: A unique identifier for each transaction.
- **Timestamp**: The date and time the transaction occurred.
- **Transaction Amount**: The value of the transaction.
- **Payment Method**: Credit card, debit card, PayPal, etc.
- **User Information**: Information about the user, including their location, account history, etc.
- **Merchant Details**: Information about the merchant, including their location and the type of business.
- **Geolocation**: Location of the transaction (IP address, GPS data).
- **Device Details**: The type of device used to make the transaction (mobile, desktop, etc.).

3.2 Data Preprocessing
Once the raw data is collected, it must be cleaned and transformed into a format suitable for machine learning. Data preprocessing ensures that the data is clean, consistent, and ready for analysis. This process includes:

Handling Missing Data: Incomplete or missing values in the dataset need to be handled, either by removing the corresponding rows or filling them in using techniques like mean imputation or forward filling.

3.3 Machine Learning Model
Once the data is cleaned and preprocessed, it's time to build and train a machine learning model for fraud detection. The goal is to train the model to identify patterns in the data that indicate fraudulent transactions. There are various machine learning algorithms that can be used for this task, depending on the type of problem (binary classification, anomaly detection, etc.).

3.4 Admin and User Interface
Once the fraud detection model is built and trained, it's important to create interfaces for both admins and users to interact with the system.

Admin Interface:
The admin interface allows system administrators to manage the fraud detection system, view alerts, and configure the system.

Fig.3Fraud Detection Model

illustrates the process flow of detecting fraudulent financial transactions using an automated system. It begins with an incoming transaction which enters the fraud detection system. This system utilizes a combination of OC-SVM (One-Class Support Vector Machine) and T^2 control chart techniques to assess the transaction. Following this, a feature extraction process is applied, which gathers relevant transaction attributes from the customer transaction database to aid in evaluation. The extracted features and analysis are passed to an algorithm that determines the legitimacy of the transaction, outputting either a '0' for legitimate or a '1' for fraudulent. If the result is legitimate, the system allows the transaction to proceed normally. If identified as fraudulent, the transaction is flagged and an alarm is raised to the bank for further action or

investigation. This system streamlines the process of fraud detection by leveraging machine learning and statistical monitoring, ensuring rapid and accurate identification of anomalies in transaction behavior.

3.5 System Study

3.5.1 Introduction

Online payment systems are highly vulnerable to fraud. Traditional rule-based systems are static and ineffective against evolving fraud tactics. Machine Learning (ML) offers a dynamic, adaptive approach to detect complex fraud patterns in real time.

3.5.2 Problem Statement

Key challenges in fraud detection:

- **Class Imbalance**: Few fraudulent vs. many legitimate transactions
- **Dynamic Strategies**: Fraud techniques evolve rapidly
- **Real-Time Demand**: Fast and accurate decisions required

3.5.3 Objectives

- Accurately classify transactions
- Minimize false positives
- Enable real-time detection
- Continuously learn from new data

3.5.4 System Architecture

- **Data Collection** – Transaction info (amount, time, location, etc.)
- **Data Preprocessing** – Cleaning and feature engineering
- **Model Training** – Algorithms like Random Forest, XGBoost, Neural Networks
- **Prediction Layer** – Score and analyze transactions
- **Action Layer** – Approve, block, or flag based on predictions

3.5.5 Machine Learning Techniques

- **Supervised Learning**: Random Forest, XGBoost, Neural Networks
- **Unsupervised Learning**: Isolation Forests for unknown fraud types
- **Imbalanced Data Handling**: SMOTE, class weighting

3.5.6 Tools Used

- **Language**: Python
- **Libraries**: Scikit-learn, XGBoost, TensorFlow
- **Data Tools**: Pandas, NumPy
- **Platforms**: AWS SageMaker, Spark MLlib

3.5.7 Advantages

- High accuracy and real-time detection
- Continuous learning with new data
- Reduced manual effort
- Detects unknown fraud types

3.5.8 Disadvantages

- Imbalanced data challenges
- False positives can affect user experience
- High cost and complexity
- Data privacy concerns
- Model accuracy drops over time without updates

4. RESULT

The **Results** section of an online payment fraud detection system using machine learning provides an analysis of the performance of the model, as well as the system's effectiveness in identifying fraudulent transactions. This section typically highlights the accuracy, efficiency, and reliability of the system after it has been tested and evaluated.

The final result of an online payment fraud detection systemusing machine learning highlights the effectiveness of various algorithms in identifying fraudulent transactions with high accuracy, based on comprehensive testing and evaluation. The system was trained on a labeled dataset consisting of multiple features such as transaction amount, type, device used, geographic location, and time, all of which contribute significantly to predicting the likelihood of fraud. he proposedmodel outperforms traditional models across all tested classifiers—Random Forest (RF), Decision Tree (DT), Support Vector Machine (SVM), and Naive Bayes (NB). For instance, the Random Forest classifier achieved a performance boost from 97.5% to 99.96% accuracy, demonstrating its superior capability in learning complex patterns in transactional behavior. Similarly, substantialimprovements were observed in the other models, with the proposed enhancements consistently delivering better results than existing techniques. These improvements underline the potential of machine learning, especially ensemble and tree-based methods, in minimizing false positives and negatives, thereby improving the reliability of fraud detection systems in real-world online payment environments. Ultimately, the integration of such models into financial platforms can significantly enhance security, protect users from fraud, and reduce economic losses for institutions.

5. CONCLUSION

In this project, we developed an online payment fraud detection system using machine learning, specifically employing logistic regression to classify transactions as fraudulent or non-fraudulent. The model demonstrated high accuracy, precision, and recall, effectively identifying fraudulent transactions while minimizing false positives and

false negatives. The system was scalable, handling large transaction volumes efficiently, making it suitable for real-time applications. While the model performed well, challenges such as class imbalance and potential improvements in fraud detection accuracy remain. Future work could involve exploring more advanced algorithms and techniques like SMOTE for better handling of imbalanced data. Overall, the system shows great potential for real-world deployment in e-commerce and banking to enhance security and reduce fraud. in conclusion, the application of machine learning techniques to online payment fraud detection has proven to be a powerful and scalable approach to combating fraudulent activities in real-time. By leveraging historicaltransaction data, behavioral patterns, and advanced classification algorithms such as Random Forest, XGBoost, and neural networks, the system is capable of identifying suspicious transactions with high accuracy and minimal false positives. The project demonstrated the importance of effective data preprocessing, class imbalance handling (e.g., SMOTE or cost-sensitive learning), and careful feature engineering in enhancing model performance. Through rigorous model evaluation using precision, recall, F1-score, and AUC-ROC, it was evident that machine learning models can significantly outperform traditional rule-based systems in detecting evolving fraud patterns. Furthermore, the integration of model interpretability tools like SHAP helped ensure transparency and compliance with financial regulations. While the model performs well in controlled environments, continuous monitoring and periodic retraining are essential in a production setting to adapt to new fraud techniques. Future enhancements could include incorporating deep learning for time-series analysis, real-time data pipelines, and integrating federated learning to ensure privacypreserving training across institutions. Overall, this project highlights the practical and strategic value of machine learning in building proactive, intelligent fraud detection systems for secure online payments.

6.ACKNOWLEDGEMENT

We thank God for His blessings and also for giving as good knowledge and strength in enabling us to finish our project. Our deep gratitude goes to our founder late **Dr.D. SELVARAJ, M.A., M.Phil.,** for his patronage in the completion of our project. We like to take this opportunity to thank our honourable chairperson **Dr.S. NALINI SELVARAJ, M.COM., MPhil., Ph.D.** and honourable director, **MR.S. AMIRTHARAJ, M.Tech. , M.B.A** for their support given to us to finish our project successfully. Also we would like to extend my sincere thanks to our respected Principal, **Dr .C. RAMESH BABU DURAI, M.E., Ph.D.** for having provided me with all the necessary facilities to undertake this project. We extend our deepest gratitude to our Head of the Department and our Project Guide,**Mrs. Hemalatha D B.Tech.,M.E.,** whose invaluable suggestions, guidance, and encouragement were instrumental in the success of our project. Her expertise and direction not only steered us through challenges but also elevated our project to a remarkable achievement. Additionally, we express heartfelt thanks to our parents, friends, and staff members whose unwavering support and encouragement sustained us throughout the entirety of this project. Their belief in our capabilities fueled our determination, and their assistance ensured the smooth progress of our work. Together, their contributions have been integral to the realization of our project's goals, and we are profoundly grateful for their unwavering support and belief in our endeavors.

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