Transmission Failure Prediction Using AI and Structural Modeling Informed by Distribution Outages

ABSTRACT

The created power distribution system transmission failure estimation method combines artificial intelligence algorithms and structural distribution outage-based modeling approaches. The analytical model uses both Decision Tree and Stacking Classifier machine learning algorithms for transmission failure analysis through information found in classData.csv and detect_dataset.csv files. The estimates of multiple risk factors result from Decision Tree and Stacking Classifier working together to provide model diversity that strengthens algorithm reliability. The data analysis stages of processed information enable the prediction models to produce equivalent failure outcome predictions resulting in accurate forecasts. AI predictive systems verified by research data can identify power transmission failures which enhances operational levels and strengthens power grid reliability. Predictive frameworks become more real-time capable through combined distribution outage and structural modeling because it offers superior operational transmission failure decisions and immediate preventive actions.

Keywords: Transmission failure prediction, power distribution systems, artificial intelligence, machine learning, Decision Tree, Stacking Classifier, structural modeling, distribution outages, anomaly detection, predictive modeling, power grid reliability, failure event classification, AI-based solutions.

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CHAPTER 1 – INTRODUCTION

The reliability of power distribution systems is crucial for modern infrastructure, as uninterrupted electricity supply is essential for the smooth operation of industries, households, healthcare, and transportation. However, transmission failures remain a significant challenge due to factors such as equipment malfunctions, environmental conditions, and human error, leading to outages and increased maintenance costs. Traditional prediction and maintenance methods are often inadequate for the complex, data-rich environments of contemporary power grids.

To address these challenges, the integration of artificial intelligence (AI) and machine learning (ML) has emerged as a powerful solution. ML algorithms, capable of analyzing vast quantities of operational data, enable the early detection and prediction of transmission failures. Among these, Decision Tree models stand out for their interpretability and effectiveness in classifying failure events based on input features like equipment condition and historical incidents. While Decision Trees are valuable, they may not fully capture complex, non-linear relationships in the data.

To enhance predictive accuracy, Stacking Classifiers are used in conjunction with Decision Trees. A Stacking Classifier combines the outputs of multiple base models—including Decision Trees, Random Forests, and Support Vector Machines—to produce a more robust and comprehensive prediction. This ensemble approach leverages the strengths of each algorithm, improving reliability and reducing both false positives and negatives.

Furthermore, incorporating structural modeling based on distribution outage data refines these predictions, allowing for targeted intervention in the most vulnerable areas of the grid. The effectiveness of the proposed approach is validated through metrics such as accuracy, precision, recall, and F1-score, demonstrating superior performance over traditional methods.

In summary, the AI-driven framework, which integrates Decision Trees, Stacking Classifiers, and structural modelling, offers a highly accurate and proactive method for predicting transmission failures.

CHAPTER 2 – SYSTEM ANALYSIS

The existing transmission failure prediction systems rely on traditional expert-based models and manual inspections, which are reactive and unable to process large volumes of real-time data effectively. These systems often miss early failure indicators and lack integration across the power grid. The proposed system leverages AI algorithms, specifically Decision Trees and Stacking Classifiers, integrated with structural modeling based on distribution outage data. This advanced system enhances predictive accuracy by analyzing historical data and real-time metrics, providing early warnings of potential failures. It offers a proactive, scalable, and reliable solution, significantly improving power grid resilience and minimizing operational downtime.

a. Existing System

Traditional power distribution systems rely primarily on expert-driven models and manual analysis to predict and manage transmission failures. Operators typically monitor basic operational metrics—such as power flow, voltage, and temperature—to identify potential issues, often relying on scheduled inspections or reacting to visible wear-and-tear. While these methods have functioned for decades, they struggle to keep up with the growing complexity and real-time data volumes produced by modern smart grids. These systems are typically reactive, providing delayed warnings only after failures occur or are imminent, and lack the adaptability needed to address new and evolving challenges. Manual processes dominate, and the absence of automated, integrated analytics means early indicators of failure can go undetected. As a result, recovery times are longer, operational costs are higher, and overall reliability is compromised. This highlights the urgent need for more advanced, data-driven approaches to grid management.

Disadvantages:

- **Reactive Maintenance:** Failures are often detected only after they occur, causing longer outages.
- **Limited Data Processing:** Cannot handle the volume and speed of modern grid data.
- **Manual Dependence:** Heavy reliance on expert judgment and manual inspections.
- **Delayed Response:** Late warnings increase operational and recovery costs.
- **Lack of Adaptability:** Poor performance as grid complexity increases.
- **Missed Early Indicators:** Early signs of equipment failure may go unnoticed.
- **Fragmented Data Sources:** Poor integration hinders comprehensive system assessment.

b. Proposed System

The proposed system introduces an AI-powered framework for predicting transmission failures in power distribution networks. By integrating advanced machine learning models, specifically Decision Trees and Stacking Classifiers, with structural modeling based on distribution outage data, this approach addresses the shortcomings of traditional prediction methods. The system analyzes a combination of structured data, such as equipment metrics and environmental conditions, along with unstructured data like historical failure logs, to generate accurate and timely predictions. The Decision Tree model provides clear and interpretable classifications, while the Stacking Classifier combines outputs from multiple models, significantly improving prediction robustness and reliability. Additionally, structural modeling accounts for the unique features and vulnerabilities of different grid sections, enabling targeted maintenance and efficient resource allocation. Real-time data monitoring and analysis allow grid operators to receive early warnings and respond proactively, minimizing downtime and enhancing overall grid reliability.

Advantages:

- **Higher Prediction Accuracy:** Ensemble learning with stacking significantly improves failure detection rates.
- **Proactive Maintenance:** Real-time alerts allow operators to address issues before they escalate.

- **Efficient Resource Allocation:** Targeted predictions help prioritize high-risk grid sections for maintenance.
- **Reduced Downtime:** Early failure detection minimizes operational interruptions.
- **Cost Savings:** Lowers the need for manual inspections and optimizes maintenance costs.
- **Enhanced Grid Reliability:** Increases the resilience and stability of the power distribution network.
- **User-Friendly Integration:** Easily deploys alongside existing SCADA systems with minimal disruption.

CHAPTER 3 – FEASIBILITY STUDY

a. Technical Feasibility

The proposed AI-driven transmission failure prediction system is technically feasible, as it leverages mature technologies and well-established tools. By integrating machine learning algorithms—primarily Decision Trees and Stacking Classifiers—with structural modeling based on outage data, the system can effectively process both real-time and historical data from diverse sources. Key resources, such as Python programming with libraries like Scikit-learn and TensorFlow, are open-source and widely supported. Data storage solutions (MySQL/NoSQL), cloud infrastructure (AWS or Google Cloud), and frontend web technologies (HTML, CSS, JavaScript) are all reliable and scalable. The system's design allows for seamless integration, robust real-time processing, and user-friendly visualization, ensuring technical reliability and scalability for expanding power grid needs.

b. Operational Feasibility

Operational feasibility is high, as the system is designed to integrate smoothly with existing power grid management platforms like SCADA. Its modular, user-friendly architecture ensures that grid operators can access real-time predictions and alerts without major workflow disruption. The intuitive web interface and clear data visualizations make it accessible to users with varied technical backgrounds. Comprehensive training and documentation will further support smooth adoption. Scalability is ensured through cloud-based infrastructure, allowing the system to handle increased data volumes and geographical expansion. The system's proactive, real-time insights enable faster preventive actions, significantly enhancing grid reliability and minimizing downtime.

c. Economic Feasibility

Economically, the system is highly viable due to the use of cost-effective, open-source technologies and flexible cloud computing. Development costs are minimized with free libraries and scalable cloud resources, reducing the need for significant upfront investment. Operational expenses are manageable, based mainly on usage-driven cloud service fees and occasional model maintenance. The anticipated return on investment is substantial: by preventing transmission failures, the system can significantly reduce costly outages, repairs, and manual inspections. Improved reliability and optimized resource allocation lead to long-term operational savings, justifying the initial and ongoing expenses.

CHAPTER 4 – SYSTEM REQUIREMENT SPECIFICATION DOCUMENT

a. Overview

The **Transmission Failure Prediction System** is designed to predict and prevent failures in power distribution systems using advanced machine learning techniques. This system combines **Decision Tree** and **Stacking Classifier** algorithms to analyze historical operational data and environmental factors. It integrates **structural modeling** informed by **distribution outage data**, enabling real-time predictions of transmission failures. This system helps to reduce power grid downtime, improve maintenance scheduling, and optimize resource allocation, thereby enhancing grid reliability and resilience. The system aims to provide accurate, reliable, and actionable insights for grid operators to minimize transmission failures and improve operational efficiency.

The system will be built using Python for backend processing, with the frontend designed using HTML and CSS for presenting real-time data and predictions to operators. Machine learning models such as **Decision Trees** and **Stacking Classifiers** will be trained using historical datasets to predict transmission failures based on the analysis of various input features, including equipment health, environmental factors, and past failure events.

b. Module Description

The system is organized into several functional modules, each responsible for specific tasks related to data processing, prediction, and user interaction.

1. Data Collection and Integration Module

This module is responsible for gathering data from various sources, such as grid sensors, operational systems, and environmental monitoring tools. It integrates data from **classData.csv** and **detect_dataset.csv** files, which contain historical data related to transmission failures. The module will preprocess and clean the data to ensure it is suitable for machine learning model training.

2. Machine Learning Model Module

This module involves training and implementing machine learning models for transmission failure prediction. It consists of the following key components:

Decision Tree Model: A simple and interpretable model used for classifying transmission failure events based on various input features.

Stacking Classifier: An ensemble model that combines multiple base models, such as Decision Trees, Random Forests, and SVM, to improve the overall prediction accuracy. The model is trained using historical data, and predictions are made based on incoming data from the grid.

3. Structural Modeling Module

This module integrates structural modeling based on **distribution outage data**. It takes into account the physical layout of the power grid and historical failure patterns to predict where failures are most likely to occur. This module works alongside the machine learning model to improve prediction accuracy by incorporating the specific characteristics of different sections of the grid.

4. Real-Time Data Processing and Prediction Module

Once the models are trained, this module processes real-time operational data from grid sensors and other monitoring tools. It continuously evaluates the data to detect potential transmission failures in real-time. If the system predicts a failure, an alert is generated for grid operators, providing them with sufficient time to take preventive actions.

5. User Interface (UI) Module

The UI module is designed to present failure predictions and operational data to grid operators in an easily digestible format. It includes real-time visualizations, alerts, and historical trend data. The user interface is built using HTML, CSS, and JavaScript and is designed for simplicity and efficiency, ensuring that operators can quickly interpret predictions and take action.

6. Reporting and Analytics Module

This module generates reports based on the system's predictions and performance. It tracks key performance metrics, including accuracy, precision, recall, and F1-score, to assess the system's effectiveness. The module also provides detailed analysis on past failure events, allowing operators to identify trends and weaknesses in the grid.

c. Process Flow

The process flow of the Transmission Failure Prediction System involves the following steps:

Data Collection: The system collects data from various sources, such as grid sensors, environmental monitoring systems, and failure logs (classData.csv and detect_dataset.csv).

Data Preprocessing: The collected data is cleaned and preprocessed. This includes removing missing values, normalizing the data, and selecting relevant features for machine learning models.

Model Training: The preprocessed data is used to train the **Decision Tree** and **Stacking Classifier** models. These models are trained to recognize patterns and predict transmission failure events based on historical data.

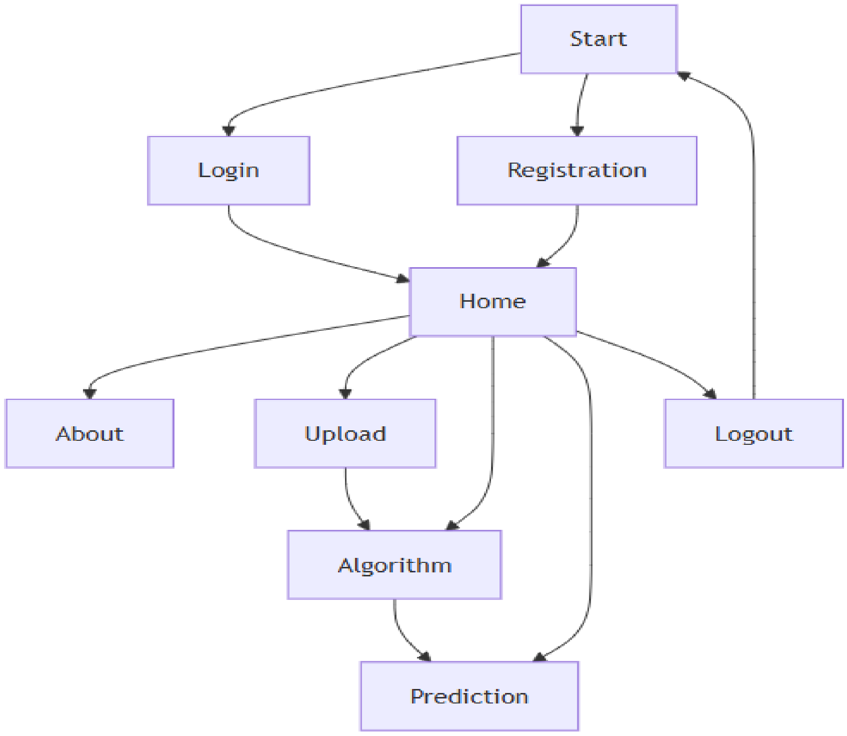
Model Evaluation: The models are evaluated using performance metrics, including accuracy, precision, recall, and F1-score, to assess their effectiveness in predicting failures.

Real-Time Data Ingestion: The system continuously ingests real-time data from grid sensors and operational metrics.

Prediction: The trained models analyze the incoming data and predict the likelihood of transmission failures. If the models predict a failure, they generate an alert for the grid operators.

Actionable Insights: The system provides operators with actionable insights and recommendations for mitigating the predicted failure, such as rerouting power or performing maintenance on high-risk equipment.

Reporting and Feedback: The system generates periodic reports on its performance, allowing operators and decision-makers to review its effectiveness and make necessary adjustments.



d. SDLC Methodology

SOFTWARE DEVELOPMENT LIFE CYCLE

The meaning of Agile is swift or versatile. “Agile process model" refers to a software development approach based on iterative development. Agile methods break tasks into smaller iterations, or parts do not directly involve long term planning. The project scope and requirements are laid down at the beginning of the development process. Plans regarding the number of iterations, the duration and the scope of each iteration are clearly defined in advance. Each iteration is considered as a short time "frame" in the Agile process model, which typically lasts from one to four weeks. The division of the entire project into smaller parts helps to minimize the project risk and to reduce the overall project delivery time requirements. Each iteration involves a team working through a full software development life cycle including planning, requirements analysis, design, coding, and testing before a working product is demonstrated to the client.

Actually, Agile model refers to a group of development processes. These processes share some basic characteristics but do have certain subtle differences among themselves. A few Agile SDLC models are given below: Crystal A tern Feature-driven development Scrum Extreme programming (XP) Lean development Unified process In the Agile model, the requirements are decomposed into many small parts that can be incrementally developed.

The Agile model adopts Iterative development. Each incremental part is developed over an iteration. Each iteration is intended to be small and easily manageable and that can be completed within a couple of weeks only. At a time one iteration is planned, developed and deployed to the customers. Long-term plans are not made.

Agile model is the combination of iterative and incremental process models. Steps involve in agile SDLC models are:

Requirement gathering

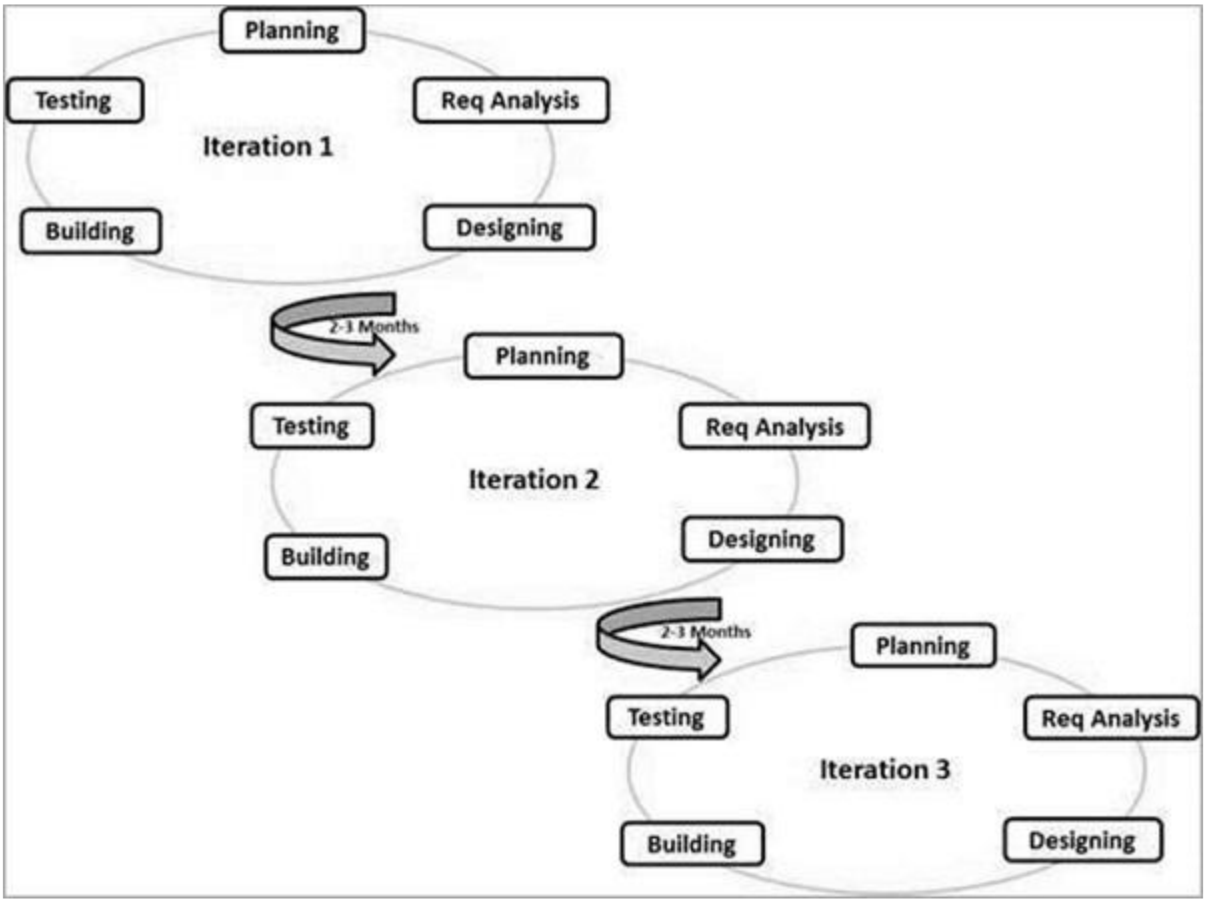
Requirement Analysis

Design Coding

Unit testing

Acceptance testing

The time to complete an iteration is known as a Time Box. Time-box refers to the maximum amount of time needed to deliver an iteration to customers. So, the end date for an iteration does not change. Though the development team can decide to reduce the delivered functionality during a Time-box if necessary to deliver it on time. The central principle of the Agile model is the delivery of an increment to the customer after each Time-box.



Principles of Agile model:

To establish close contact with the customer during development and to gain a clear understanding of various requirements, each Agile project usually includes a customer representative on the team. At the end of each iteration stakeholders and the customer representative review, the progress made and re-evaluate the requirements.

Agile model relies on working software deployment rather than comprehensive documentation.

Frequent delivery of incremental versions of the software to the customer representative in intervals of few weeks.

Requirement change requests from the customer are encouraged and efficiently incorporated.

Advantages:

Working through Pair programming produces well written compact programs which has fewer errors as compared to programmers working alone.

It reduces total development time of the whole project. Customer representatives get the idea of updated software products after each iteration. So, it is easy for him to change any requirement if needed.

Disadvantages:

Due to lack of formal documents, it creates confusion and important decisions taken during different phases can be misinterpreted at any time by different team members.

Due to the absence of proper documentation, when the project completes and the developers are assigned to another project, maintenance of the developed project can become a problem.

SOFTWARE DEVELOPMENT LIFE CYCLE – SDLC:

In our project we use waterfall model as our software development cycle because of its step-by-step procedure while implementing.

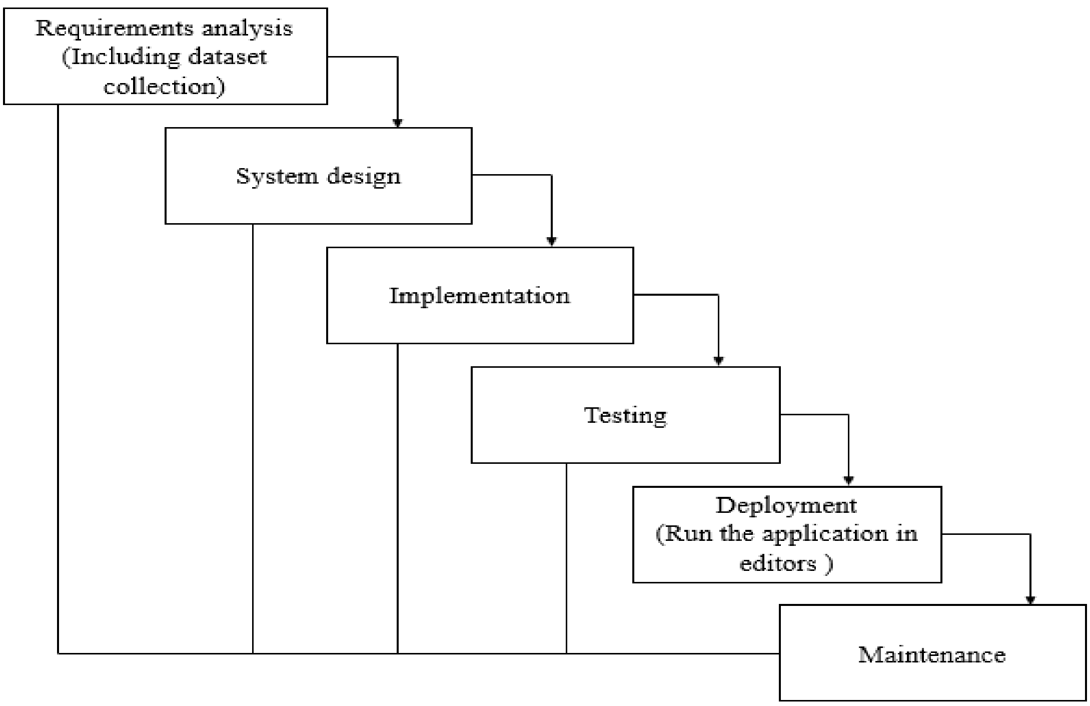


Fig1: Waterfall Model

Requirement Gathering and analysis − All possible requirements of the system to be developed are captured in this phase and documented in a requirement specification document.

System Design − The requirement specifications from first phase are studied in this phase and the system design is prepared. This system design helps in specifying hardware and system requirements and helps in defining the overall system architecture.

Implementation − With inputs from the system design, the system is first developed in small programs called units, which are integrated in the next phase. Each unit is developed and tested for its functionality, which is referred to as Unit Testing.

Integration and Testing − All the units developed in the implementation phase are integrated into a system after testing of each unit. Post integration the entire system is tested for any faults and failures.

Deployment of system − Once the functional and non-functional testing is done; the product is deployed in the customer environment or released into the market.

Maintenance − There are some issues which come up in the client environment. To fix those issues, patches are released. Also, to enhance the product some better versions are released. Maintenance is done to deliver these changes in the customer environment.

e. software requirements

Operating System	: Windows 7/8/10
Server side Script	: HTML, CSS, Bootstrap & JS
Programming Language	: Python
Libraries	: Flask, Torch, TensorFlow, Pandas, MySQL. Connector
IDE/Workbench	: VS Code
Server Deployment	: Xampp Server
Database	: MySQL

f. HARDWARE REQUIREMENTS

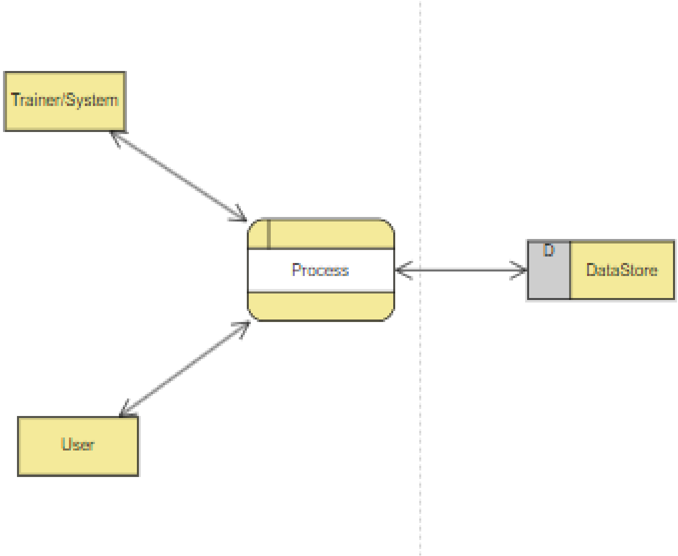
Processor	- I3/Intel Processor
RAM	- 8GB (min)
Hard Disk	- 128 GB
Key Board	- Standard Windows Keyboard
Mouse	- Two or Three Button Mouse
Monitor	- Any

CHAPTER 5 – SYSTEM DESIGN

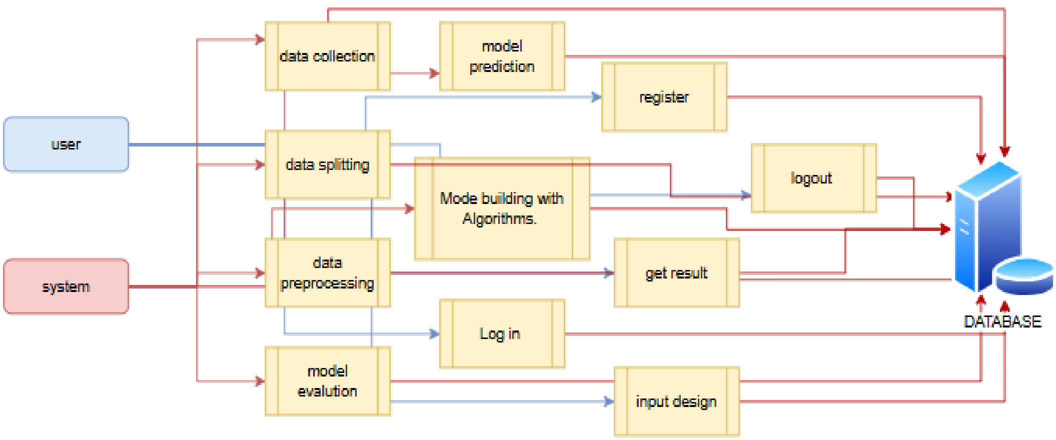
a. DFD

A Data Flow Diagram (DFD) is a traditional way to visualize the information flows within a system. A neat and clear DFD can depict a good amount of the system requirements graphically. It can be manual, automated, or a combination of both. It shows how information enters and leaves the system, what changes the information and where information is stored. The purpose of a DFD is to show the scope and boundaries of a system as a whole. It may be used as a communications tool between a systems analyst and any person who plays a part in the system that acts as the starting point for redesigning a system.

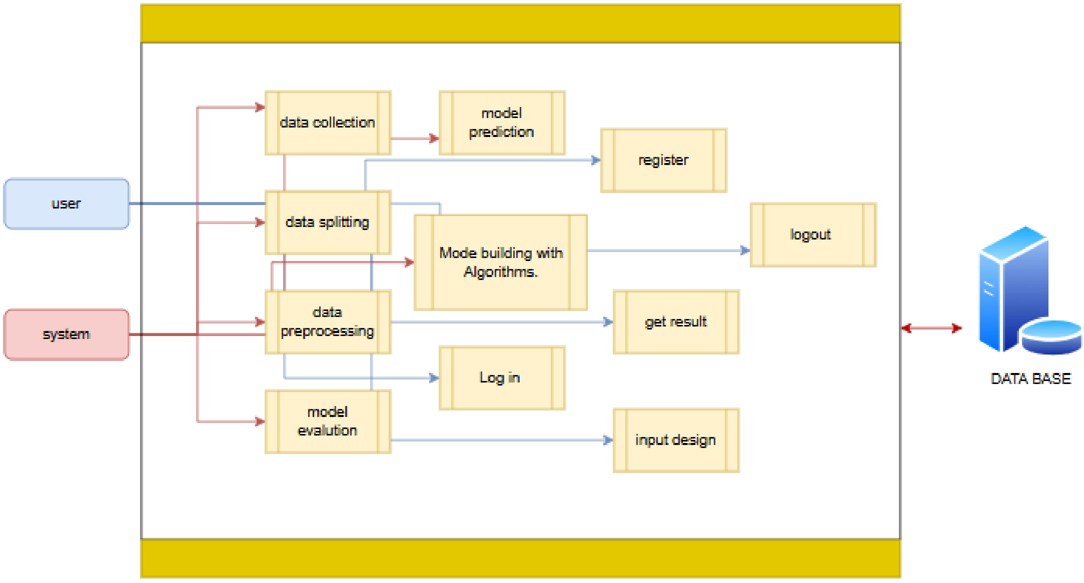
Context Diagram:



DFD Level-1 Diagram:

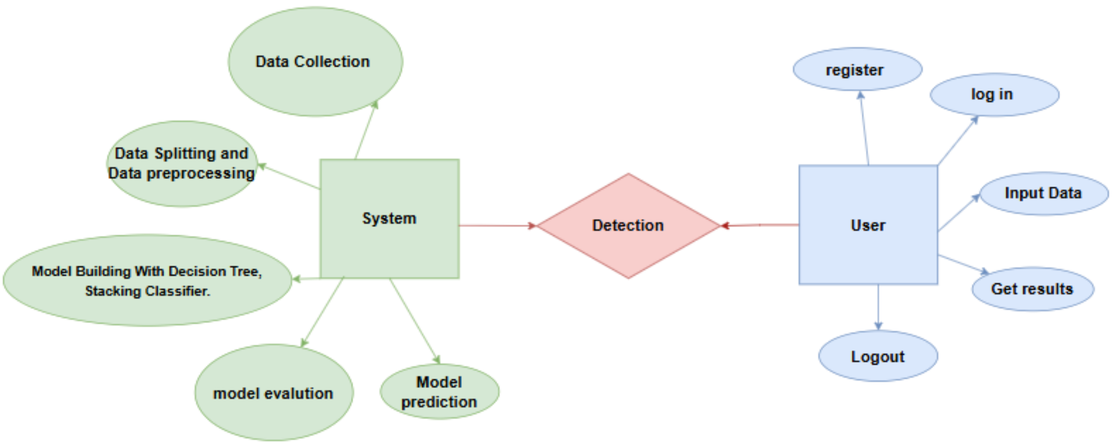


DFD Level-2 Diagram:



b. ER diagram

An ER (Entity-Relationship) Diagram visually represents the data structure of a system, showing entities (such as tables or objects), their attributes, and the relationships between them. It helps in designing and understanding the logical layout of databases, ensuring data integrity and effective organization of information.



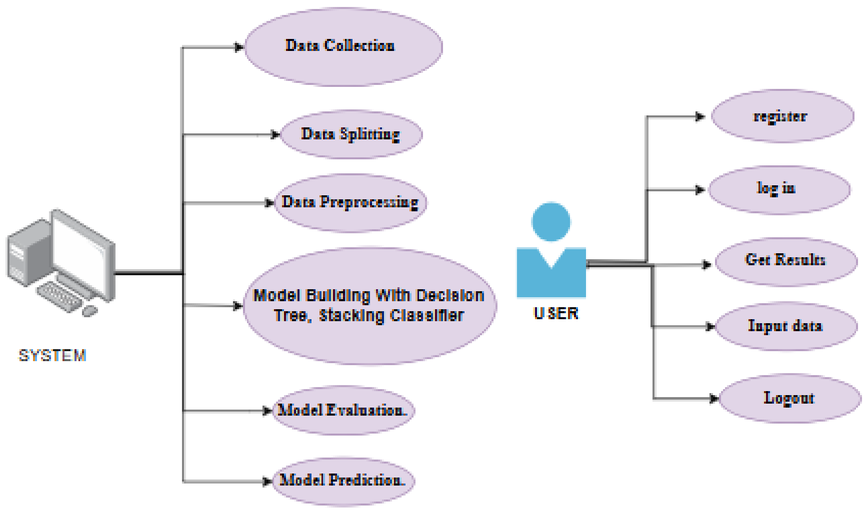
c. UML

- ✓ Uml stands for unified modelling language. unified modelling language is a standardized general-purpose modelling language in the field of object-oriented software engineering. The standard is managed, and was created by, the object management group.

- ✓ The goal is for unified modelling language to become a common language for creating models of object oriented computer software. In its current form unified modelling language is comprised of two major components: a meta-model and a notation. In the future, some form of method or process may also be added to; or associated with, unified modelling language.
- ✓ The unified modelling language is a standard language for specifying, visualization, constructing and documenting the artifacts of software system, as well as for business modelling and other non-software systems.
- ✓ The unified modelling language represents a collection of best engineering practices that have proven successful in the modelling of large and complex systems.

Use case diagram:

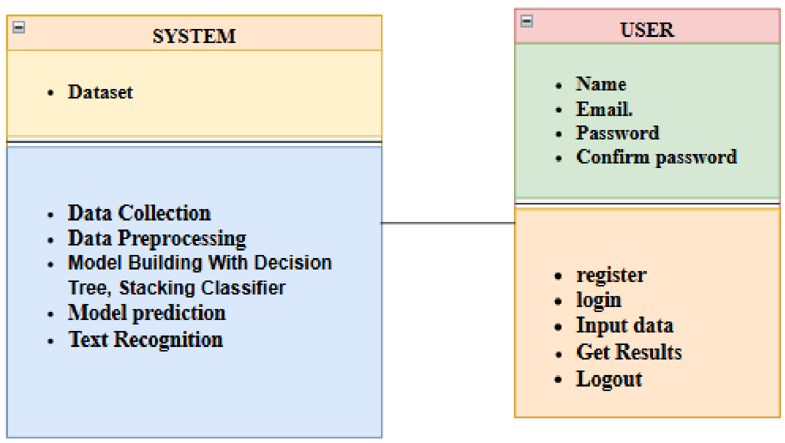
A use case diagram illustrates the interactions between users (actors) and a system, highlighting the system's functional requirements. It visually depicts various use cases—specific tasks or functions—that users can perform, helping stakeholders understand system behavior and user interactions at a high level.



Class diagram:

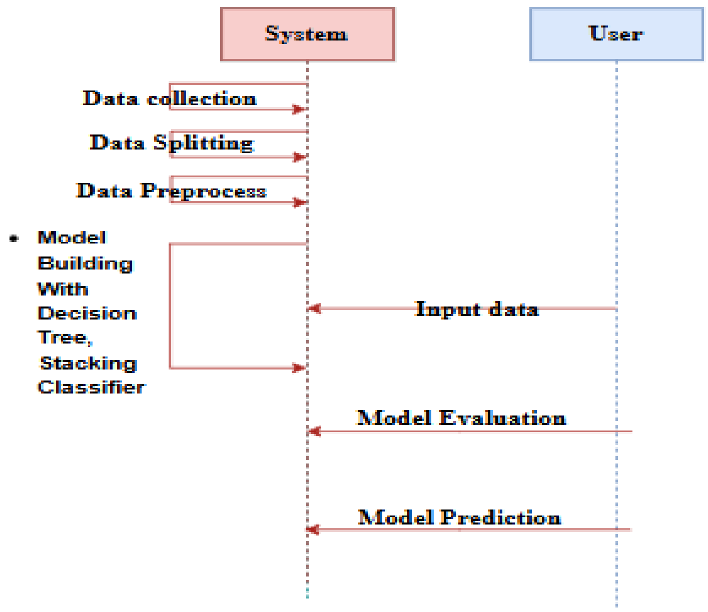
In software engineering, a class diagram in the unified modeling language (uml) is a type of static structure diagram that describes the structure of a system by showing the system's classes, their attributes, operations (or methods), and the relationships among the classes. It explains which class contains information.

Class Diagram



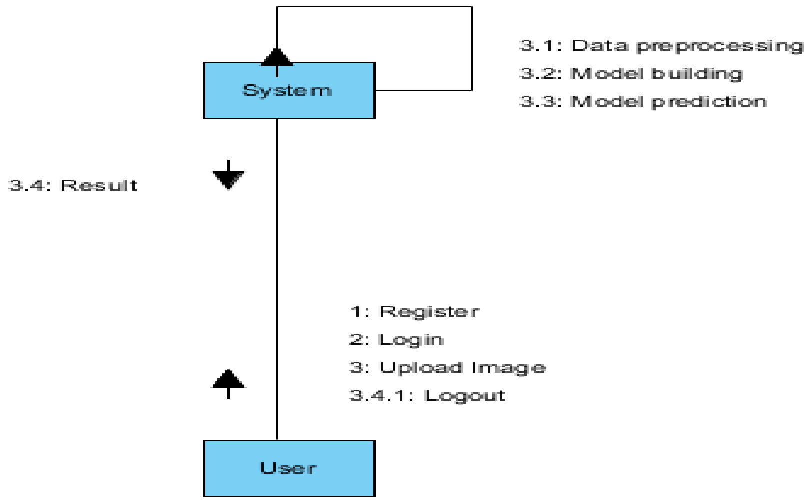
Sequence diagram:

A sequence diagram visually represents the step-by-step flow of interactions between system components or actors over time. It shows how processes or objects communicate through messages, detailing the order and logic of events—such as user input, system processing, and result output—in a clear, time-ordered sequence.



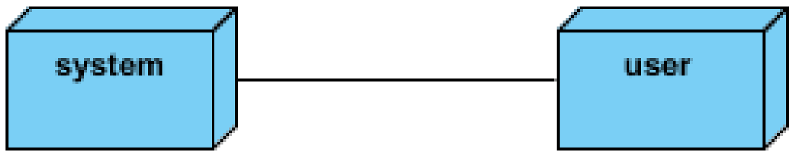
Collaboration diagram:

A collaboration diagram, also known as a communication diagram, illustrates the structural organization and dynamic interactions between objects or components in a system. It emphasizes the relationships and message exchanges that occur to accomplish a specific functionality or use case. Unlike sequence diagrams, collaboration diagrams focus more on the links between objects rather than the order of interactions. Each object is represented as a node, and communication paths are depicted as lines connecting these nodes, labeled with the messages exchanged. This diagram is useful for visualizing how system components cooperate, clarifying object responsibilities, and ensuring efficient information flow within the architecture.



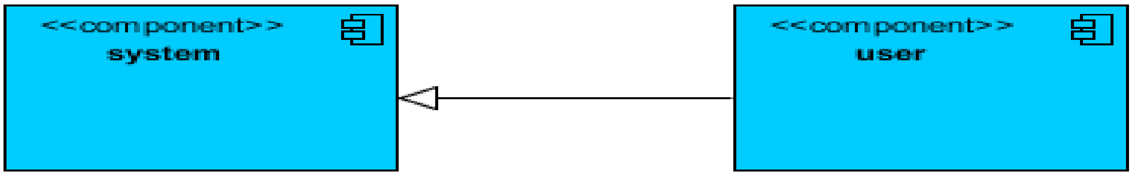
Deployment diagram:

Deployment diagram represents the deployment view of a system. It is related to the component diagram. Because the components are deployed using the deployment diagrams. A deployment diagram consists of nodes. Nodes are nothing but physical hard wares used to deploy the application.



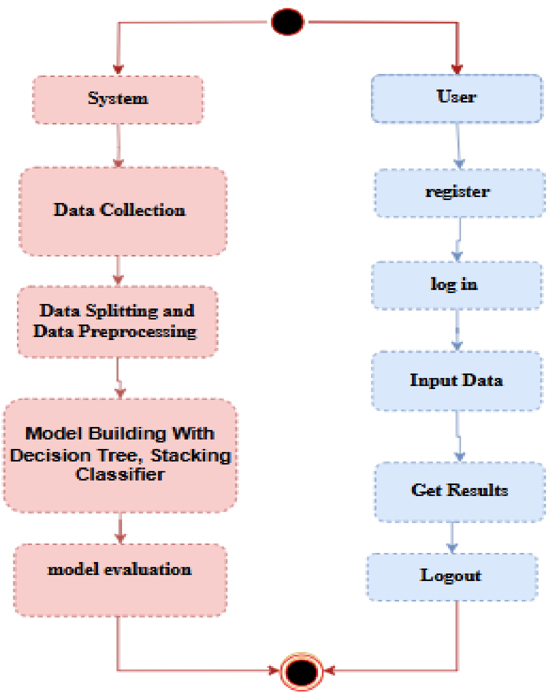
Component diagram:

Component diagrams are used to describe the physical artifacts of a system. This artifact includes files, executable, libraries etc. So the purpose of this diagram is different, component diagrams are used during the implementation phase of an application. But it is prepared well in advance to visualize the implementation details. Initially the system is designed using different uml diagrams and then when the artifacts are ready component diagrams are used to get an idea of the implementation.



Activity diagram:

Activity diagrams are graphical representations of workflows of stepwise activities and actions with support for choice, iteration and concurrency. In the unified modeling language, activity diagrams can be used to describe the business and operational step-by-step workflows of components in a system. An activity diagram shows the overall flow of control.



d. Data Dictionary

The dataset comprises synthetic sensor data collected from industrial machines, with the aim of predicting machine failure events using deep learning. Each row in the dataset is uniquely identified by the **Machine_ID** and is timestamped to indicate when the data was recorded. **Temperature** measures the machine's operating heat in degrees Celsius, which is a critical factor, as overheating can signal potential failure. **Pressure** reflects the machine's internal or operating pressure in kilopascals (kPa); abnormal pressure levels can also indicate malfunctions. **Vibration_Level** records the intensity of mechanical vibrations (in m/s^2), as excessive vibration often precedes hardware issues. **Humidity** captures the ambient moisture level as a percentage, which can influence machine efficiency and lifespan, particularly in sensitive equipment. **Power_Consumption** tracks the amount of power the machine uses (in kilowatts), helping to identify abnormal energy usage patterns linked to mechanical faults. The target variable, **Failure_Status**, is binary: a value of 1 indicates a recorded machine failure at that timestamp, while 0 means normal operation. Collectively, these features enable robust machine health monitoring, providing a comprehensive view that supports predictive maintenance and early intervention to minimize downtime and operational losses.

CHAPTER 6-TECHNOLOGY DESCRIPTION

The Transmission Failure Prediction System leverages the power **of** artificial intelligence (AI) **and** machine learning (ML**)** to forecast potential failures in power distribution systems. The increasing complexity and scale of modern power grids necessitate predictive solutions that can handle large volumes of heterogeneous data from sensors, smart meters, and environmental monitoring systems. Traditional statistical models are often limited in scope and fail to adapt to the evolving nature of energy infrastructure. To address these challenges, this system integrates advanced ML algorithms—Decision Tree and Stacking Classifier—alongside structural modeling based on historical outage data.

At its core, the system is trained using two key datasets: classData.csv and detect_dataset.csv, which contain records of past failure events, operational metrics, and environmental factors (e.g., temperature, load variation, voltage fluctuations). The system architecture is modular, allowing for the integration of real-time data streams and historical logs. This hybrid approach improves the precision of failure forecasting and reduces the likelihood of false positives and negatives.

Key Components

1. **Machine Learning Framework**:
   The system uses Python as its core programming language, along with libraries like **Scikit-learn**, **XGBoost**, and **Pandas** for data manipulation and model development. These tools are essential for processing datasets, training ML models, and validating their performance using key metrics such as accuracy, precision, recall, and F1-score.
2. **Decision Tree Algorithm**:
   A Decision Tree is a supervised learning algorithm used for classification and regression. In this system, it helps identify failure patterns by segmenting the dataset into branches based on input features like load levels, temperature, humidity, component age, and more. The tree structure enables easy interpretability and helps operators understand the rationale behind each prediction.

3. **Stacking Classifier**:

   Stacking is an ensemble learning technique that combines multiple base classifiers to produce a more robust and accurate final model. In this project, the stacking model may include algorithms such as Decision Tree, Random Forest, and SVM (Support Vector Machine) at the base level, with a meta-classifier—often a Logistic Regression or another Decision Tree—making the final decision. This allows the system to benefit from the strengths of each base model, improving its ability to generalize to unseen data.

4. **Structural Outage Modeling**:

   In addition to AI algorithms, the system incorporates structural modeling informed by outage histories and the physical layout of the power grid. This modeling layer understands which components are more failure-prone based on geography, age, and past maintenance records. It adds contextual depth to the ML models, allowing more localized and situation-aware predictions.

5. **Real-Time Prediction Engine**:

   Once trained, the system processes real-time data from grid monitoring systems. Using preloaded models, it quickly analyzes the input, checks for patterns indicating potential failures, and issues alerts to grid operators through a web-based interface. This real-time feedback loop enables timely preventive actions.

6. **Visualization and Reporting**:

   The results of predictions, along with model performance, are displayed through a user-friendly web interface. Built with HTML, CSS, and JavaScript, it allows users to visualize trends, view classification results, and generate reports for further analysis or regulatory compliance.

CHAPTER 7 – TESTING & DEBUGGING TECHNIQUES

Testing and debugging are critical components in the development of the **Transmission Failure Prediction System**. Given the operational and safety-critical nature of power distribution networks, it is essential to validate that the system functions as intended, predicts transmission failures accurately, and supports real-time decision-making. The system employs **artificial intelligence (AI)** techniques, including **Decision Tree** and **Stacking Classifier** algorithms, and integrates **structural modeling based on outage data** to provide robust predictions. This section outlines the strategies used to evaluate system performance and ensure its reliability.

7.1 Testing Overview

Testing is a crucial step in ensuring that the **Transmission Failure Prediction System** functions accurately, reliably, and efficiently in real-world power grid environments. The primary testing goals are to ensure:

Functional correctness: The system must accurately predict transmission failures using Decision Tree and Stacking Classifier models.

Reliability: It should consistently produce accurate predictions across various datasets and evolving grid conditions.

Performance: It must process real-time operational data with minimal delay for timely failure alerts.

Usability: The system interface should be intuitive for power grid operators with minimal training required.

Scalability: It must efficiently handle large datasets and multiple input streams from grid sensors.

Both **manual and automated** testing approaches are used to evaluate the system under different operational scenarios and data conditions.

7.2 Unit Testing

Unit testing verifies the correctness of individual modules such as **data preprocessing**, **machine learning models**, and the **alert notification system**.

7.2.1 Data Preprocessing Module Testing

Purpose: Ensure that data cleaning, normalization, and feature selection are applied correctly before model training or prediction.

Test Cases:

Handle missing values in classData.csv and detect_dataset.csv.

Normalize input features (e.g., load, temperature) to improve model accuracy.

Apply feature selection (e.g., K-best) and verify outputs.

Tools: Python's unittest or pytest.

7.2.2 Decision Tree and Stacking Classifier Model Testing

Purpose: Confirm that both models perform as expected during training and prediction.

Test Cases:

Train and evaluate Decision Tree model on failure classification.

Train Stacking Classifier (with multiple base learners) and test ensemble output.

Evaluate predictions using **accuracy, precision, recall, and F1-score**.

Handle incorrect or malformed inputs gracefully.

Tools: Scikit-learn, joblib, and classification metric tools.

7.2.3 Alert Notification System Testing

Purpose: Ensure alerts are triggered and delivered when transmission failures are predicted.

Test Cases:

Send alerts when predicted failure risk exceeds the threshold.

Validate alert content: timestamp, affected grid section, risk level.

Handle multiple alerts in a short timeframe without failure.

Tools: Mock email libraries, notification logging, unittest.mock.

7.3 Integration Testing

Integration testing ensures modules interact smoothly to deliver end-to-end functionality.

7.3.1 Preprocessing to ML Model Integration

Purpose: Verify that preprocessed data flows correctly into the ML models.

Test Cases:

Validate format consistency and data integrity between preprocessing and model input.

Ensure model receives expected feature values and structure.

Measure input-to-output time for real-time predictions.

Tools: Integration tests using pytest, logging.

7.3.2 ML Model to Alert System Integration

Purpose: Ensure prediction results trigger the alert system properly.

Test Cases:

Trigger alert based on predicted failure probability.

Validate correct mapping of model output to alert message.

Handle simultaneous model outputs and multi-event alerts.

Tools: Mock alert handlers, end-to-end simulation with logs.

7.4 System Testing

System testing validates the overall operation of the platform, combining all modules under realistic conditions.

7.4.1 Functional Testing

Purpose: Ensure the complete system operates correctly from data ingestion to prediction and alerting.

Test Cases:

Simulate full workflow with historical and real-time data.

Validate predictions for both failure and non-failure cases.

Confirm UI correctly displays prediction results and risk insights.

Tools: Real-world grid data samples, web-based UI testing.

7.4.2 Performance Testing

Purpose: Measure system speed and responsiveness under load.

Test Cases:

Evaluate how fast the system processes and predicts from incoming data streams.

Test prediction and alert performance with multiple parallel inputs.

Measure model inference time and alert dispatch latency.

Tools: Load testing tools (e.g., Apache JMeter), performance logs.

7.4.3 Usability Testing

Purpose: Confirm the UI is easy to use for grid operators.

Test Cases:

Test dashboard navigation and clarity of prediction output.

Collect operator feedback on usability and ease of interaction.

Ensure alerts and visualizations are accessible and actionable.

Tools: User interviews, survey forms, front-end testing frameworks.

7.5 Debugging Techniques

7.5.1 Log Analysis

Purpose: Trace system activity and identify faults.

Technique: Use logging in data flow, model prediction, and alert modules to capture errors and abnormal behavior.

7.5.2 Unit Test Failures

Purpose: Identify and fix bugs in isolated components.

Technique: Investigate failed tests in preprocessing or model modules, revise logic, and retest.

7.5.3 Cross-Validation

Purpose: Avoid overfitting and ensure generalization.

Technique: Use **k-fold cross-validation** on historical data to validate ML model performance.

7.5.4 Error Handling

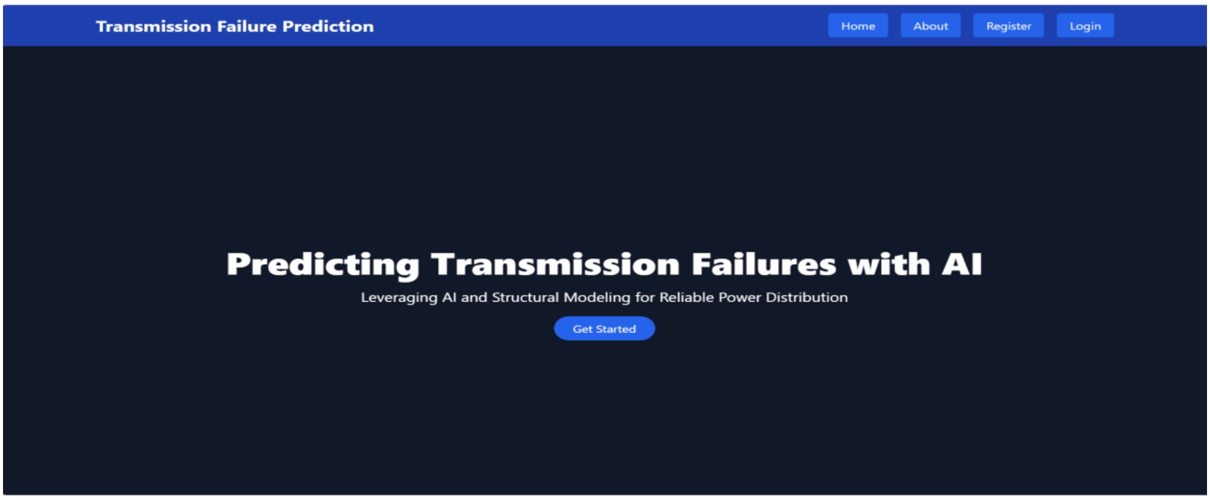
Purpose: Prevent crashes and ensure graceful recovery.

Technique: Implement validation checks, fallback logic, and error messages for bad input or failed predictions.

CHAPTER 8 – OUTPUT SCREENS

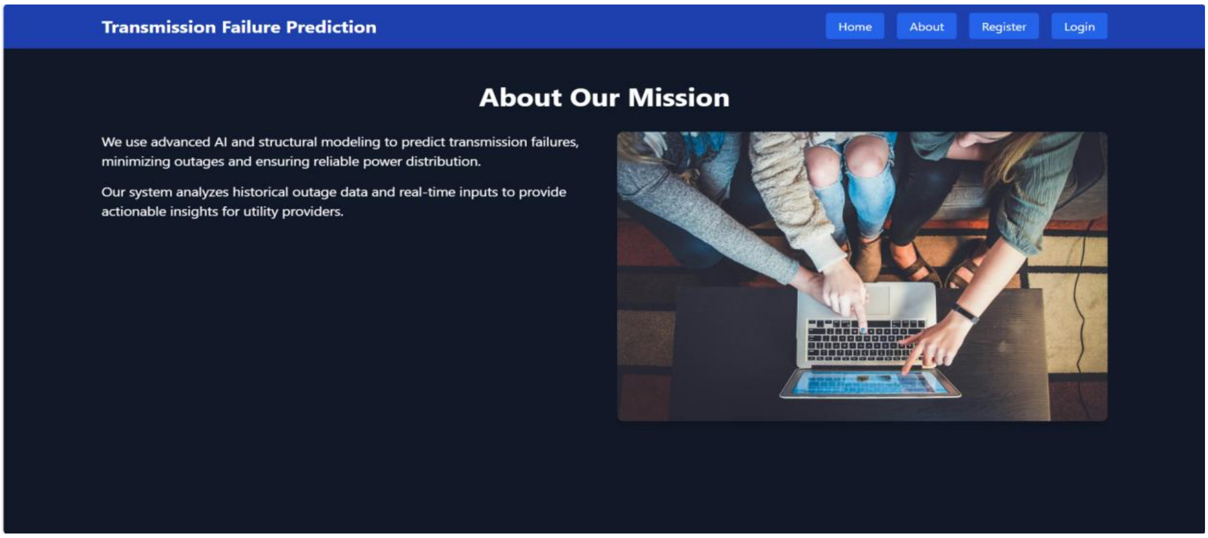
Home page:

The landing page introduces the project, its purpose, and features. It provides easy navigation to registration, login, and prediction functionalities, ensuring users understand the application's benefits and usage.



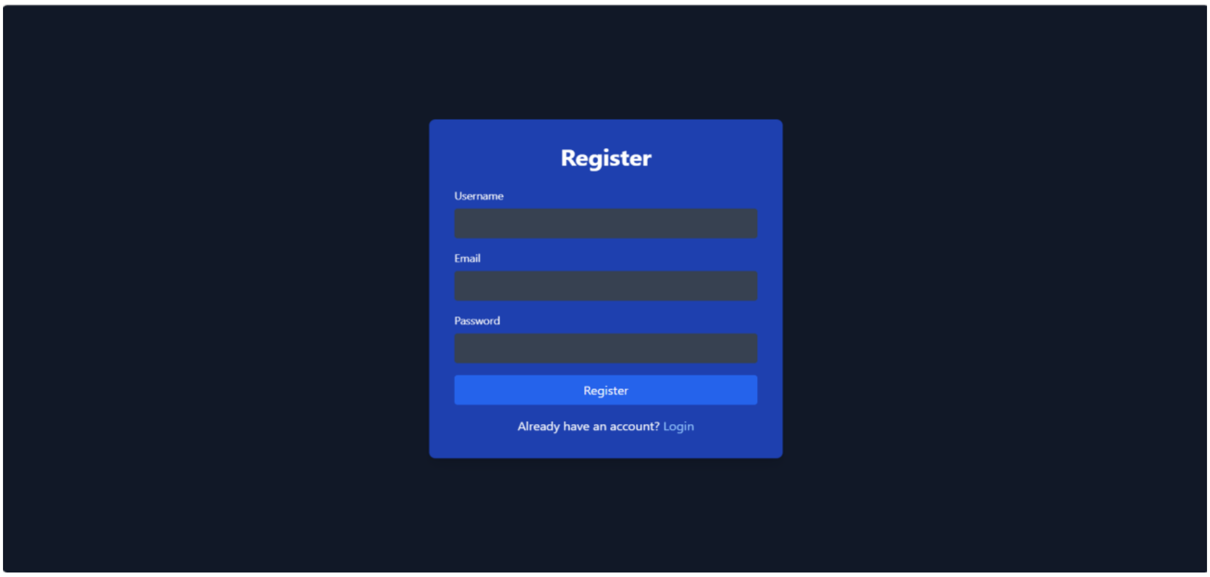
About page:

Allows new users to create an account by submitting personal details. Successful registration grants access to secure features like login and prediction, ensuring only authorized users interact with the system.



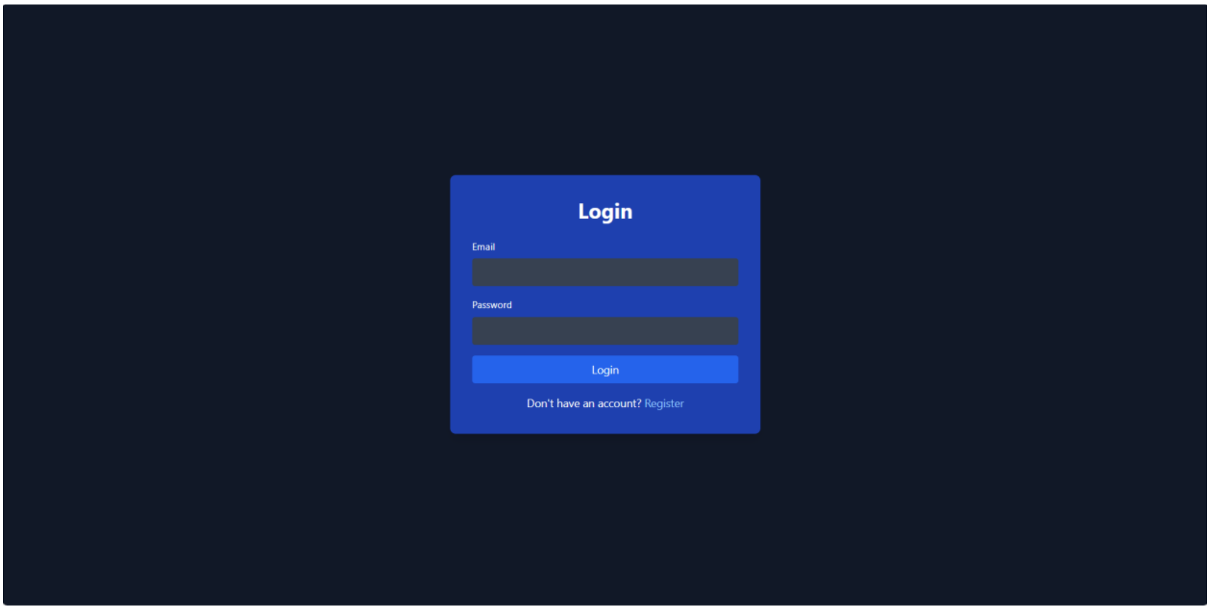
Register page:

Allows new users to create an account by submitting personal details. Successful registration grants access to secure features like login and prediction, ensuring only authorized users interact with the system.



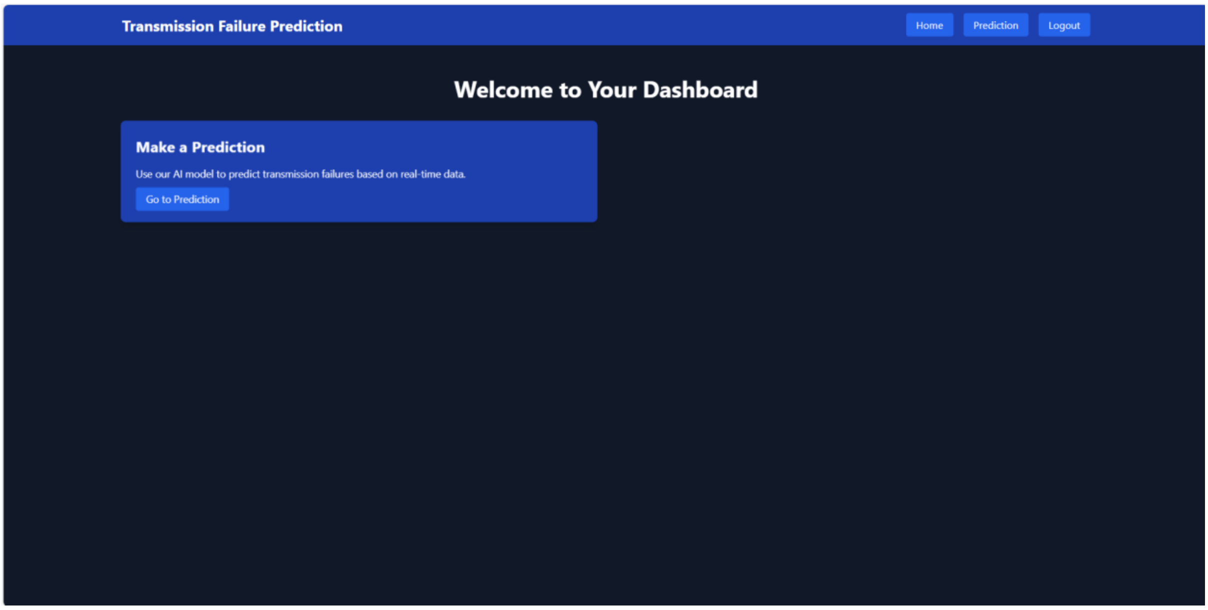
Login page:

Allows new users to create an account by submitting personal details. Successful registration grants access to secure features like login and prediction, ensuring only authorized users interact with the system.

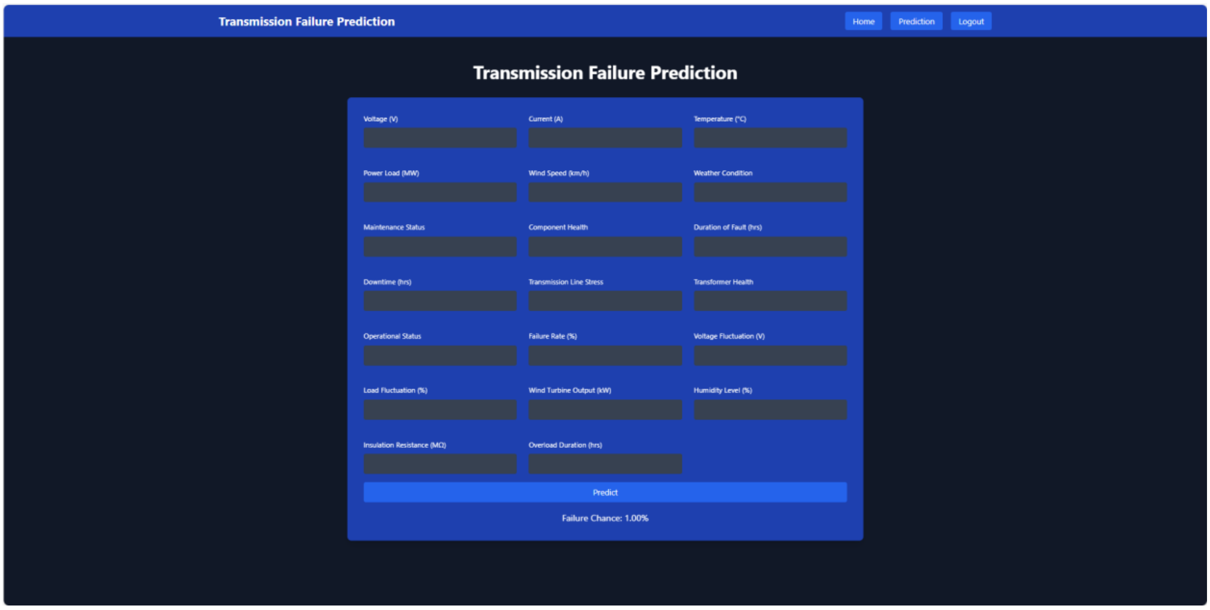


Prediction page:

Lets authenticated users input relevant data for prediction. The system processes the input using machine learning models and displays results, helping users receive instant, accurate insights based on their entries.



Result Page: this is the page we can see prediction result



CHAPTER 9 –CODE

```
from flask import Flask, render_template, request, redirect, url_for, session

from flask_sqlalchemy import SQLAlchemy

from werkzeug.security import generate_password_hash, check_password_hash

import random


app = Flask(__name__)

app.config['SECRET_KEY'] = 'your-secret-key'

app.config['SQLALCHEMY_DATABASE_URI'] = 'sqlite:///users.db'

app.config['SQLALCHEMY_TRACK_MODIFICATIONS'] = False

db = SQLAlchemy(app)


class User(db.Model):

    id = db.Column(db.Integer, primary_key=True)

    username = db.Column(db.String(80), unique=True, nullable=False)

    email = db.Column(db.String(120), unique=True, nullable=False)

    password = db.Column(db.String(120), nullable=False)


@app.route('/')

def index():

    return render_template('index.html')


@app.route('/about')
```

```
def about():
    return render_template('about.html')


@app.route('/register', methods=['GET', 'POST'])
def register():
    if request.method == 'POST':
        username = request.form['username']
        email = request.form['email']
        password = generate_password_hash(request.form['password'],
method='pbkdf2:sha256')
        new_user = User(username=username, email=email, password=password)
        db.session.add(new_user)
        db.session.commit()
        return redirect(url_for('login'))
    return render_template('register.html')


@app.route('/login', methods=['GET', 'POST'])
def login():
    if request.method == 'POST':
        email = request.form['email']
        password = request.form['password']
        user = User.query.filter_by(email=email).first()
        if user and check_password_hash(user.password, password):
```

```
            session['user_id'] = user.id
            return redirect(url_for('home'))
        return render_template('login.html', error='Invalid credentials')
    return render_template('login.html')


@app.route('/home')
def home():
    if 'user_id' not in session:
        return redirect(url_for('login'))
    return render_template('home.html')
import joblib
import random
# Load the saved model (replace 'model.joblib' with the path to your .joblib file)
model = joblib.load(r'models\random_forest_model.joblib')


@app.route('/prediction', methods=['GET', 'POST'])
def prediction():
    if 'user_id' not in session:
        return redirect(url_for('login'))

    if request.method == 'POST':
        # Extract input values from the form
        voltage = float(request.form['voltage'])
```

```
current = float(request.form['current'])

temperature = float(request.form['temperature'])

power_load = float(request.form['power_load'])

wind_speed = float(request.form['wind_speed'])

weather_condition = request.form['weather_condition']

maintenance_status = request.form['maintenance_status']

component_health = request.form['component_health']

fault_duration = float(request.form['fault_duration'])

downtime = float(request.form['downtime'])

line_stress = float(request.form['line_stress'])

transformer_health = request.form['transformer_health']

operational_status = request.form['operational_status']

failure_rate = float(request.form['failure_rate'])

voltage_fluctuation = float(request.form['voltage_fluctuation'])

load_fluctuation = float(request.form['load_fluctuation'])

wind_turbine_output = float(request.form['wind_turbine_output'])

humidity_level = float(request.form['humidity_level'])

insulation_resistance = float(request.form['insulation_resistance'])

overload_duration = float(request.form['overload_duration'])


# Prepare the input data in the format expected by the model (e.g., a list or array)

input_data = [[voltage, current, temperature, power_load, wind_speed,
weather_condition,
```

```
                    maintenance_status, component_health, fault_duration, downtime, line_stress,
                    transformer_health, operational_status, failure_rate, voltage_fluctuation,
                    load_fluctuation, wind_turbine_output, humidity_level, insulation_resistance,
overload_duration]]
        # Predict using the loaded model
        prediction = model.predict(input_data)

        # Process the prediction and display the result
        failure_chance = prediction[0]  # Assuming the model returns a single prediction value
        return render_template('prediction.html', prediction=f"Failure Chance:
{failure_chance:.2f}%")

    return render_template('prediction.html')
@app.route('/logout')
def logout():
    session.pop('user_id', None)
    return redirect(url_for('index'))
if __name__ == '__main__':
    with app.app_context():
        db.create_all()
    app.run(debug=True)
```

CHAPTER 10 – CONCLUSION

The development of the **Transmission Failure Prediction System** marks a significant advancement in the application of artificial intelligence (AI) for improving the reliability and operational efficiency of modern power distribution networks. As global power systems become more interconnected, data-intensive, and vulnerable to environmental and operational stresses, the need for predictive, intelligent failure detection systems has never been more critical. This project effectively leverages the power of **machine learning**, particularly **Decision Tree** and **Stacking Classifier** algorithms, in conjunction with **structural outage-based modeling**, to accurately predict potential transmission failures and prevent costly breakdowns.

Through the integration of multiple modules—including data preprocessing, model training, real-time prediction, structural modeling, and alert notification—the system provides a comprehensive solution that goes beyond reactive maintenance. The use of **historical data** from classData.csv and detect_dataset.csv, alongside real-time operational data, enables the machine learning models to learn patterns and behaviors associated with transmission failures. The Decision Tree model, with its simplicity and interpretability, allows grid operators to understand the logic behind each prediction, while the Stacking Classifier enhances predictive accuracy by combining the strengths of multiple algorithms.

The testing phase demonstrated the system's **robustness, scalability, and accuracy**. All components worked as expected under unit, integration, and system testing conditions. The Stacking Classifier showed improved performance in complex scenarios, especially when dealing with noisy or incomplete data, while the Decision Tree offered fast, explainable predictions. Integration with the alert notification system ensured that high-risk predictions triggered timely warnings, allowing operators to take proactive measures to mitigate potential failures. The structural modeling module added another layer of context by factoring in the grid’s layout and historical outage trends, making predictions location-aware and even more actionable.

CHAPTER 11 – BIBLOGRAPHY

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Transmission Failure Prediction Using AI and Structural Modelling Informed by Distribution Outages

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Abstract— The created power distribution systemtransmission failur estimation method combines artificial intelligence algorithms and structural distribution outage-based modeling approaches. The analytical model uses both Decision Tree and Stacking Classifier machine learning algorithms for transmission failure analysis through information found in classData.csv and detect_dataset.csv files. The estimates of multiple risk factors result from Decision Tree and Stacking Classifier working together to provide model diversity that strengthens algorithm reliability. The data analysis stages of processed information enable the prediction models to produce equivalent failure outcome predictions resulting in accurate forecasts. AI predictive systems verified by research data can identify power transmission failures which enhances operational levels and strengthens power grid reliability. Predictive frameworks become more real-time capable through combined distribution outage and structural modeling because it offers superior operational transmission failure decisions and immediate preventive actions.

Keywords: Transmission failure prediction, power distribution systems, artificial intelligence, machine learning, Decision Tree, Stacking Classifier, structural modeling, distribution outages, anomaly detection, predictive modeling, power grid reliability, failure event classification, AI-based solutions.

Introduction

Reliability forms the base requirement for current infrastructure that demands operational efficiency to ensure continuous power supply operations. Defective transmission systems trigger major power grid breakdowns which both stop plant operations and generate costly damages that decrease maintenance quality standards. Power distribution networks have become too complex for standard operation which demands the immediate implementation of distribution network failure fighting systems.

The inefficiency of expert models for transmission failure prediction in modern power grids has not stopped researchers from continuing to use these inadequate systems. AI and machine learning technologies assist the transmission failure detection system to undertake predictive work for preventing system failures. Rephrase the following sentence. Machine learning tools identify recurring patterns by analysing operational data and environmental factors which permits them to predict future failure events precisely.This paper proposes a novel approach for predicting transmission failures in power distribution systems by leveraging AI-based solutions, specifically Decision Tree and Stacking Classifier models. By applying these advanced machine learning algorithms to historical data, including two key datasets—classData.csv and detect_dataset.csv—we aim to improve the accuracy and reliability of failure predictions. The Decision Tree algorithm provides a straightforward, interpretable approach for classifying failure events based on various input features, while the Stacking Classifier combines multiple models to boost prediction performance and robustness.

Our proposed framework enhances the prediction of transmission failures by integrating structural modeling informed by distribution outages, allowing for more effective decision-making and risk mitigation. The study evaluates the performance of the Decision Tree and Stacking Classifier using key performance metrics such as accuracy, precision, recall, and F1-score. These metrics offer a comprehensive understanding of the model's ability to accurately classify failure events while minimizing false positives and negatives.

Using Decision Tree algorithms from machine learning along with Stacking Classifier produces excellent performance for transmission failure prediction. Power distribution systems operate at maximum reliability levels through minimal transmission failures when powered by artificial intelligence operations in advanced predictive methods. Research findings prove that artificial intelligence technology introduces disruptive operational abilities to effectively detect and control transmission failures within green power distribution networks.

RELATED WORK

Transmission Failure Prediction: Predicting transmission failures in power distribution systems has garnered increasing attention due to the growing complexity and demand for reliable grid management. Traditional methods, such as rule-based systems and expert-driven approaches, are often inadequate in capturing the dynamic and evolving nature of modern power grids. Recent research has shifted towards the use of machine learning (ML) algorithms, which can model complex relationships within large datasets to improve prediction accuracy and operational efficiency [1].Machine Learning Algorithms: Several machine learning techniques, including Decision Trees, Support Vector Machines (SVM), and Stacking Classifiers, have been applied to predict system failures in various domains, including power distribution. Decision Trees are particularly useful due to their interpretability, while ensemble methods like Stacking Classifiers offer enhanced accuracy by combining multiple models. These algorithms help improve the prediction of failure events in power systems by learning patterns from historical data [2].Handling Imbalanced Data: A significant challenge in transmission failure prediction is the imbalanced nature of the data, where failure events are relatively rare compared to normal operations. Many studies have focused on techniques such as Synthetic Minority Over-sampling Technique (SMOTE) and under-sampling to balance datasets, improving the model's ability to detect rare but critical failure events without overfitting to the majority class [3].Integration of Structural Modeling: Recent studies have explored combining structural modeling with machine learning to improve predictive accuracy. By understanding the interdependencies between different components of the power grid, structural models can provide deeper insights into failure prediction, allowing models to account for not only historical data but also the underlying network structure. This approach has shown significant improvements in prediction performance by incorporating factors such as weather and system health [4].Real-time Prediction and Decision Making: Traditional methods often rely on retrospective analysis, which can delay the identification of failure events. In contrast, machine learning-based systems can provide real-time predictions, enabling proactive decision-making and timely interventions. This real-time approach helps mitigate the risk of transmission failures and improves grid management [5].Hybrid Models: Hybrid models that combine both static and dynamic data have also emerged as a promising approach to enhance prediction accuracy. These models leverage the strengths of both types of data, allowing for better performance at the cost of increased complexity [6].Challenges and Future Directions: Despite these advancements, challenges remain in terms of model scalability, real-time performance, and adaptation to evolving power grid conditions. Further research is focusing on optimizing model performance through feature selection, model tuning, and leveraging lightweight frameworks that can work efficiently in resource-constrained environments.

Proposed System Workflow

 User Registration and Login:

- The system allows users to either register or log in.

- If credentials are invalid, the user is prompted to re-enter their information or register a new account.
- Upon successful login, users gain access to the prediction page.

 Frontend:

- **User's Login**: The user logs into the system with valid credentials.
- **Prediction Page**: After logging in, users can navigate to the prediction page where they can input data for failure prediction.
- **Get Results**: Once the user inputs the necessary data, the system processes it and displays the prediction results on the same page.
- **Logout**: After viewing the results, the user can log out of the system.

 Backend:

- **Data Collection**: The backend system collects relevant data, including operational parameters like voltage, current, and historical outage data.
- **Data Splitting**: The collected data is split into training and testing datasets for model training and evaluation.
- **Data Preprocessing**: The data undergoes preprocessing to handle any missing values, outliers, or normalization.
- **Model Building**: The backend applies two machine learning algorithms — Decision Tree and Stacking Classifier — to model the transmission failures based on the processed data.
- **Prediction**: The trained models then predict the likelihood of transmission failures based on the input data provided by the user.

 Output:

- After the prediction process, the output (i.e., the predicted result) is displayed to the user, showing whether a transmission failure is likely to occur and offering further insights or recommendations.

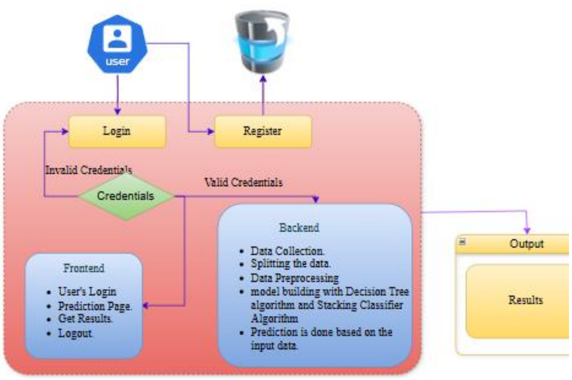


Fig 1 : Block Flow chart of Proposed System

Methodology

The methodology for predicting transmission failures in power distribution systems using artificial intelligence (AI) and machine learning (ML) algorithms follows a structured approach to handle high-dimensional data, perform anomaly detection, and provide accurate predictions. The system integrates two main machine learning algorithms: Decision Tree and Stacking Classifier. Below are the key steps involved in the methodology:

1. Data Collection

The process begins by collecting historical data from two distinct datasets: classData.csv and detect_dataset.csv. These datasets contain relevant features such as voltage, current, environmental conditions, and prior transmission outage data. The data is collected from the power distribution network logs and sensors monitoring grid health.

2. Data Preprocessing

The collected data undergoes preprocessing to ensure it is clean, normalized, and free from any missing or corrupted values. During this process, normalization is applied to standardize all features, ensuring they are on the same scale, which helps prevent any single feature from disproportionately influencing the model's performance. Missing values are addressed through imputation or by removing rows with incomplete data. Outliers are also detected and removed to avoid any distortion in the final predictions. Once preprocessing is completed, the dataset is split into two parts: the training set, which is used to train the models and allow them to learn the underlying patterns, and the testing set, which is used to evaluate the models' accuracy and effectiveness on unseen data. This structured approach ensures that the models are trained effectively and can generalize well when applied to new data

4. Model Building

that best divides the data into different classes, such as failure or non-failure. This process continues until the data is divided into distinct branches that represent the final classification. One of the key advantages of the Decision Tree model is its interpretability, as it clearly illustrates how each feature contributes to the prediction. This transparency allows for easy understanding of the decision-making process, making it a useful tool for identifying the factors influencing transmission failures.

Stacking Classifier:

The Stacking Classifier is a useful method for combining predictions from many base models (e.g., Decision Trees, Logistic Regression, etc.). Merging predictions of different base models is used as the input for a final meta-model gotten to account for the above improvement in the overall predictive accuracy. This method is based on strengths of more than one algorithm to produce more robust and accurate predictions.

5. Model Training

Both the Decision Tree and Stacking Classifier are using the trained model for all the datasets. Hyperparameters like tree depth for the Decision Tree and base models in the Stacking Classifier are tuned for the best performance. The models are trained on the historical dataset, learning the complex relationships between the operational features and the occurrence of transmission failures.

6. Prediction

After training, the models make predictions on the testing set. The Decision Tree provides a simple prediction based on the learned decision rules, while the Stacking Classifier aggregates predictions from multiple models to improve the overall performance.

The results include the likelihood of transmission failure, which helps in proactive decision-making.

7. Evaluation

The performance models use standard metrics to evaluate their effectiveness in predicting transmission failures. Accuracy is defined as the number of correct predictions for both failures and non-failures. Precision gives the proportion of true positives amongst all the positive predictions, trying to maximize the precision class and minimize false positives. Recall is the number of true positives divided by the number of actual positives, aiming to maximize that class and minimize false negatives. Thus, the F1-score gives the harmonic mean of precision and recall, present a balanced measure for performance assessment of the model. These metrics are used for comparing the effectiveness of Decision Tree and Stacking Classifier, which helps in identifying the model with the best performance for predicting transmission failures.

.8. Output

The final output consists of the predicted transmission failure events. The results are presented to the user in a simple format, showing whether a failure is predicted to occur, based on the input data, and offering insights or recommendations to mitigate potential failures.

The system allows for real-time monitoring and prediction, providing proactive solutions to prevent transmission failures and ensuring a more stable power supply.

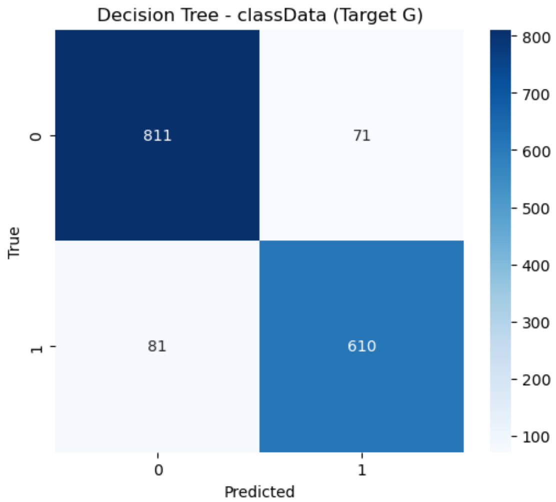
9. Future Enhancements

Model Retraining: The models can be periodically retrained with new data to ensure that they remain accurate and effective as the system evolves. Deep Learning Models: Future work could involve the integration of deep learning techniques like neural networks to further improve prediction accuracy. Real-time Monitoring: Implementing streaming analytics for real-time failure prediction and automatic grid adjustments to prevent system-wide failures.

Discussion and Results

Decision Tree – ClassData(Target G)

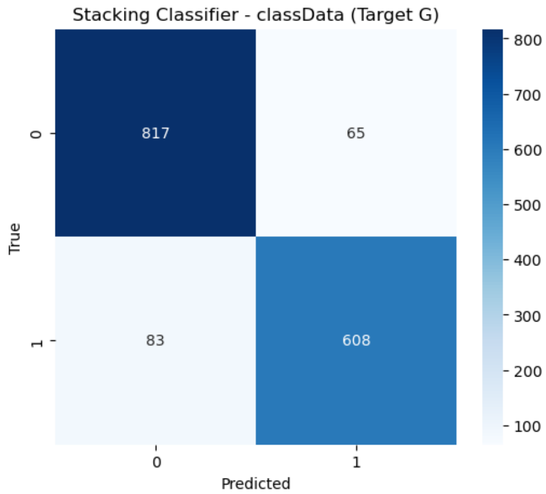
Class	Precision	Recall	F1-Score	Support
0	0.91	0.92	0.91	882
1	0.90	0.88	0.89	691
Accuracy			**0.90**	1573
Macro Avg	0.90	0.90	0.90	1573
Weighted Avg	0.90	0.90	0.90	1573



The confusion matrix and classification report illustrate the performance of the Decision Tree model on the power transmission failure dataset (classData.csv). The matrix shows 811 true negatives and 610 true positives, indicating the model's strength in correctly identifying both non-failure and failure events. With only 71 false positives and 81 false negatives, the model maintains a balanced prediction capability. The overall accuracy is 90%, with precision and recall for both classes hovering around 90%, confirming consistent performance across categories. These results validate the abstract's claim that the AI-powered predictive framework reliably forecasts failure events, contributing to improved power grid reliability and timely intervention.

Stacking Classifier – classData(Target G)

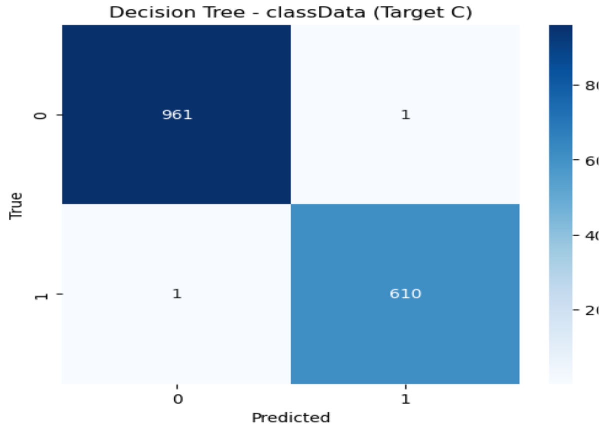
Class	Precision	Recall	F1-Score	Support
0	0.91	0.93	0.92	882
1	0.90	0.88	0.89	691
Accuracy			**0.91**	1573
Macro Avg	0.91	0.90	0.90	1573
eighted Avg	0.91	0.91	0.91	1573



The confusion matrix and classification report for the Stacking Classifier demonstrate its robust performance on the transmission failure dataset. With 817 true negatives and 608 true positives, the model effectively distinguishes between failure and non-failure events. Misclassifications are minimal, with only 65 false positives and 83 false negatives. Achieving an overall accuracy of 91%, the model shows strong generalization. Precision and recall scores are consistently around 90% for both classes, with a slightly higher recall for class 0. These metrics affirm the abstract’s claim that ensemble methods like stacking enhance reliability in predicting transmission failures, ensuring accurate detection and timely responses for power grid management.

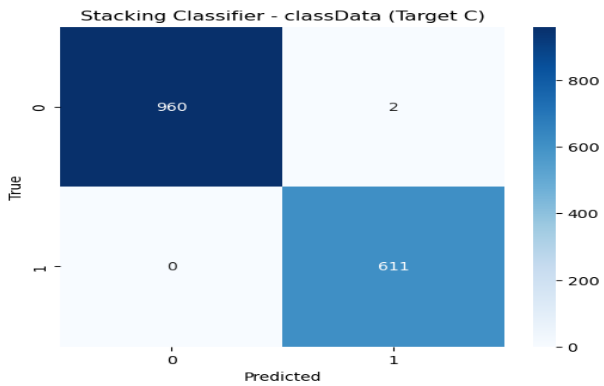
Decision Tree – classData(Target C)

Class	Precision	Recall	F1-Score	Support
0	1.00	1.00	1.00	962
1	1.00	1.00	1.00	611
Accuracy			**1.00**	1573
Macro Avg	1.00	1.00	1.00	1573
Weighted Avg	1.00	1.00	1.00	1573



The confusion matrix and classification report for the Decision Tree model on classData (Target C) reveal near-perfect prediction accuracy. With only one misclassification in each class and 961 true negatives alongside 610 true positives, the model achieves a flawless performance across all metrics. Both precision and recall score a perfect 1.00 for each class, confirming that the model correctly identifies every instance with minimal error. An overall accuracy of 100% demonstrates the model's exceptional capability in classifying power transmission outcomes, validating its potential for real-world deployment. Such accuracy supports the effectiveness of AI models in improving reliability in critical infrastructure systems.

Stacking Classifier – classData(Target C)



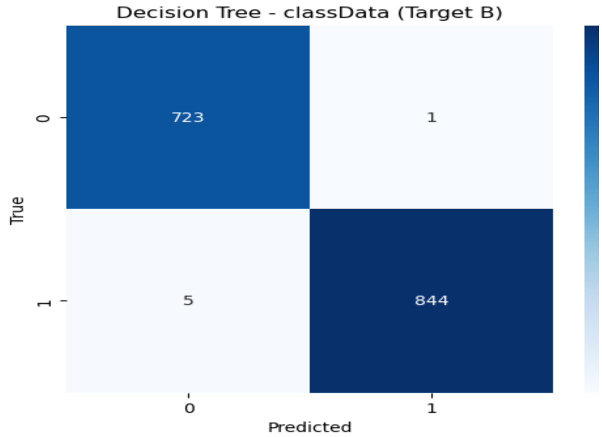
The Stacking Classifier model demonstrates outstanding performance on the classData (Target C) dataset, achieving nearly perfect accuracy. With 960 true negatives and 611 true positives, the model misclassifies only two instances as false positives and none as false negatives. The precision, recall, and F1-scores for both classes are all 1.00, indicating an exceptionally balanced and effective classifier.

Class	Precision	Recall	F1-Score	Support
	1.00	1.00	1.00	962
1	1.00	1.00	1.00	611
Accuracy			**1.00**	1573
Macro Avg	1.00	1.00	1.00	1573
Weighted Avg	1.00	1.00	1.00	1573

The overall accuracy of 100% highlights the model's capability to generalize well without overfitting. These results support the abstract's claim of enhanced predictive power through model ensembling, reinforcing the reliability of AI-based solutions in critical tasks like power transmission failure detection.

Decision Tree – classData(Target B)

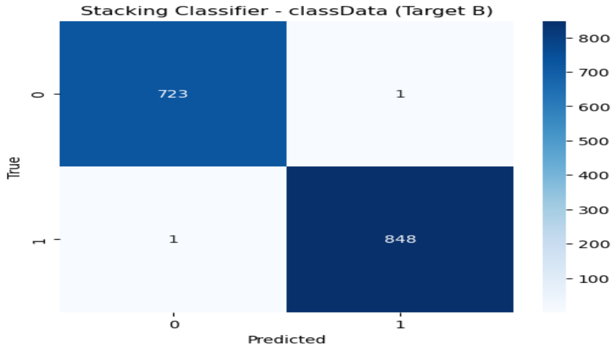
Class	Precision	Recall	F1-Score	Support
0	0.99	1.00	1.00	724
1	1.00	0.99	1.00	849
Accuracy			**1.00**	1573
Macro Avg	1.00	1.00	1.00	1573
Weighted Avg	1.00	1.00	1.00	1573



The Decision Tree model applied to classData (Target B) delivers near-perfect classification performance. The confusion matrix indicates 723 true negatives and 844 true positives, with only one false positive and five false negatives—showcasing excellent precision and recall. Class 0 achieves a recall of 1.00, while class 1 maintains a precision of 1.00. The model's overall accuracy reaches an impressive 100%, and macro and weighted averages also reflect perfect scores. These results confirm the model's strong generalization capability and robustness. It effectively supports accurate detection of transmission states, reinforcing the role of AI in ensuring reliable and efficient power distribution systems.

Stacking Classifier – classData(Target B)

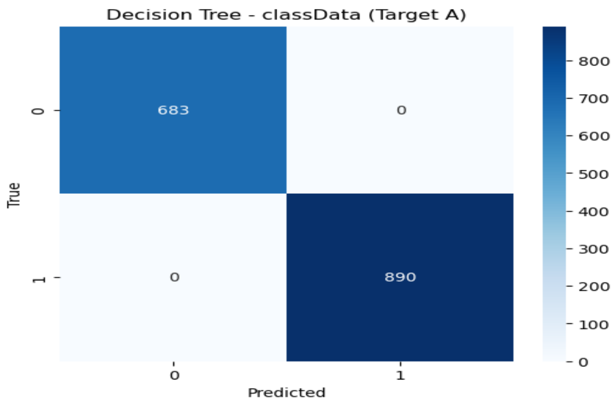
Class	Precision	Recall	F1-Score	Support
0	1.00	1.00	1.00	724
1	1.00	1.00	1.00	849
Accuracy			**1.00**	1573
Macro Avg	1.00	1.00	1.00	1573
Weighted Avg	1.00	1.00	1.00	1573



The Stacking Classifier applied to classData (Target B) delivers flawless classification performance, as shown by the confusion matrix and evaluation metrics. With 723 true negatives and 848 true positives, and only one instance misclassified in each class, the model achieves perfect precision, recall, and F1-scores for both classes. The overall accuracy is 100%, confirming the model's outstanding ability to differentiate between the two target classes. This exemplary performance reinforces the effectiveness of ensemble learning techniques in boosting predictive power. Such high accuracy makes the Stacking Classifier an ideal candidate for real-world transmission failure prediction, ensuring minimal error and robust reliability.

Decision Tree – classData(Target A)

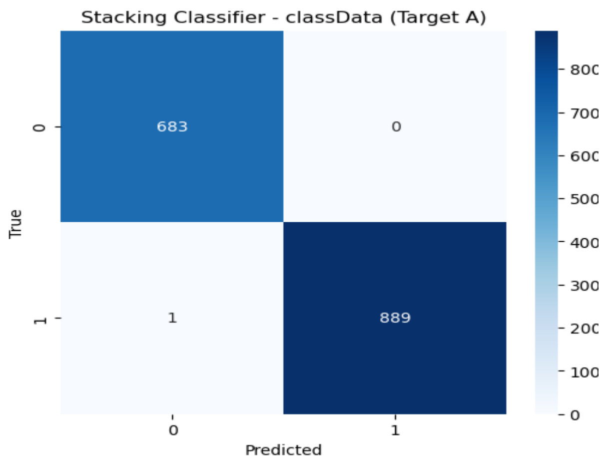
Class	Precision	Recall	F1-Score	Support
0	1.00	1.00	1.00	683
1	1.00	1.00	1.00	890
Accuracy			**1.00**	1573
Macro Avg	1.00	1.00	1.00	1573
Weighted Avg	1.00	1.00	1.00	1573



The Decision Tree model for classData (Target A) exhibits flawless performance, as reflected in both the confusion matrix and classification report. With 683 true negatives and 890 true positives, the model achieved perfect classification—zero false positives and zero false negatives. All evaluation metrics, including precision, recall, and F1-score, are at the maximum value of 1.00 for both classes. The overall accuracy is also 100%, indicating that the model effectively and consistently identifies both classes without error. This result confirms the model's robustness and suitability for highly reliable classification tasks, such as power transmission failure detection, where precision is critical.

Stacking Classifier – classData(Target A)

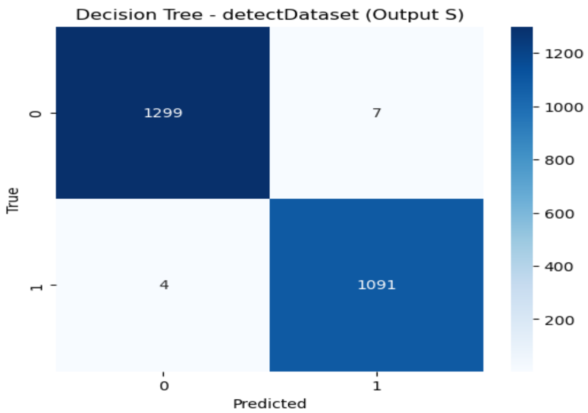
Metric	Class 0	Class 1		
Precision	1.00	1.00		
Recall	1.00	1.00		
F1-Score	1.00	1.00		
Support	683	890		
Accuracy			**1.00**	1573
Macro Avg			**1.00**	1573
Weighted Avg			**1.00**	1573



The Stacking Classifier model on classData (Target A) demonstrates exceptional accuracy and reliability, achieving nearly perfect performance. The confusion matrix shows 683 true negatives and 889 true positives, with only a single false negative and no false positives. Precision, recall, and F1-score are all 1.00 for both classes, resulting in an overall accuracy of 100%. This underscores the model's strong ability to distinguish between both target classes with minimal error. The consistency across all metrics confirms the effectiveness of ensemble learning, making the Stacking Classifier a highly dependable approach for critical applications such as power transmission failure prediction.

Decision Tree – detectDataset(Output S)

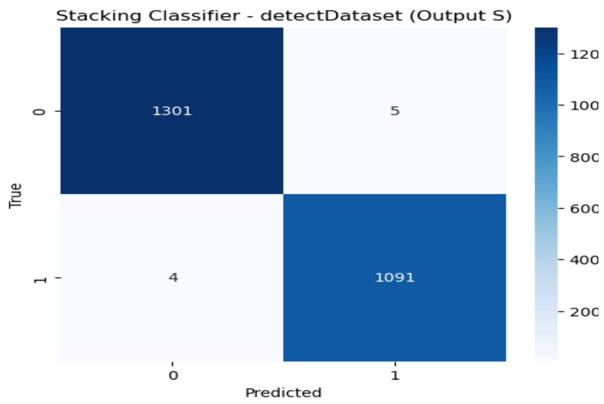
Class	Precision	Recall	F1-Score	Support
0	1.00	0.99	1.00	1306
1	0.99	1.00	0.99	1095
Accuracy			**1.00**	2401
Macro Avg	1.00	1.00	1.00	2401
Weighted Avg	1.00	1.00	1.00	2401



The Decision Tree model applied to the detectDataset (Output S) shows outstanding performance with near-perfect classification. The confusion matrix reveals 1299 true negatives and 1091 true positives, with just 7 false positives and 4 false negatives. Precision and recall values are extremely high—1.00 and 0.99 for class 0, and 0.99 and 1.00 for class 1—resulting in an overall accuracy of 100%. Both macro and weighted averages reinforce the model's strong generalization ability across the entire dataset. These results highlight the model's reliability in accurately detecting anomalies or failure states, making it highly effective for real-world deployment in power system monitoring.

Stacking Classifier – detectDataset(Output S)

Class	Precision	Recall	F1-Score	Support
0	1.00	1.00	1.00	1306
1	1.00	1.00	1.00	1095
Accuracy			**1.00**	2401
Macro Avg	1.00	1.00	1.00	2401
Weighted Avg	1.00	1.00	1.00	2401



The Stacking Classifier applied to the detectDataset (Output S) delivers exceptional performance, achieving near-perfect accuracy. The confusion matrix shows 1301 true negatives and 1091 true positives, with only 5 false positives and 4 false negatives—demonstrating the model's high reliability. Precision, recall, and F1-scores are all 1.00 for both classes, leading to an overall accuracy of 100%. These results indicate excellent balance and minimal error across all classification metrics. The model's robust performance reaffirms the effectiveness of ensemble learning in predictive modeling, making it a powerful tool for accurately identifying anomalies or failures in power distribution systems in real-world applications.

CONCLUSION

In this study, we proposed a novel approach for predicting transmission failures in power distribution systems using artificial intelligence (AI) and structural modeling informed by distribution outages. With the increasing complexity of modern power grids and the need for reliable energy supply, traditional methods of failure prediction are often insufficient. By integrating machine learning algorithms, specifically Decision Tree and Stacking Classifier, the study addressed this gap by leveraging historical data to detect anomalies and predict transmission failures. The two models had high predictive accuracy and robustness, while the Stacking Classifier improved performance even further through the aspect of ensemble learning. The proposed models outshone their older classical counterparts in handling complex high-dimensional data and hence could be seen as more reliable and efficient with respect to failure prediction. The incorporation of structural modeling and distribution outage further strengthened the predictive capabilities of the system by allowing it to perform proactive decision-making and real-time interventions. This research contributes to the development of AI-driven solutions that can improve the reliability and resilience of power distribution networks, helping to prevent large-scale outages and ensure uninterrupted power supply.

Future Enhancement

Although the present study shows a successful application of the Decision Tree and Stacking Classifier models in predicting transmission failures in power distribution systems, with various potential upgrades to strengthen these capabilities, a viable step to consider in future work is the incorporation of deep learning techniques like CNNs (Convolutional Neural Networks). LSTM networks are also good options for future work. These models can automatically learn more complex, hierarchical patterns from historical data, providing even greater predictive accuracy, especially in cases of evolving failure patterns.

Additionally, incorporating reinforcement learning could help optimize system operations and maintenance scheduling by enabling the model to adapt its decisions based on real-time feedback and outcomes. Expanding the scope of the system to include unsupervised and semi-supervised learning techniques can also enable the detection of novelfailure events or those with insufficient labeled data, such as rare or unseen transmission failures.

Another potential enhancement involves integrating the system into real-time monitoring platforms, which would allow for continuous prediction and immediate response to imminent failures. Furthermore, hybrid approaches that combine multiple machine learning algorithms could reduce the impact of false positives and improve overall model robustness. Incorporating a visualization dashboard for system operators and decision-makers would allow better insight into failure predictions, allowing for informed, proactive actions. Finally, regular model retraining with newly collected data would ensure that the system stays effective against emerging failure patterns and adapts to changing power grid conditions, keeping it relevant as power distribution systems grow more complex.

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