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(Deemed to be University under section 3 of UGC Act, 1956)
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Department of Computer Science and Engineering

Artificial Intelligence and Machine Learning

ADVANCED LEARNER'S INTERDISCIPLINARY PROJECTS

AY - 2024 - 2025

INDEX

Crack Detection and Severity Assessment using YOLOv8

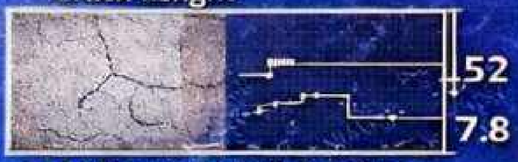
Presented an advanced solution using **YOLOv8** for automated crack detection and severity **assessment** in concrete structures.

Key Steps

1. **Crack Detection**
   Bounding box, ROI segmentation
2. **Region Cropping**
   ROI segmentation
3. **Skeletonization**
   for Crack Length
4. **Measuring Crack Width**
   Orthogonal width

Dataset & Training

4000 images split: **80% train,** 10% Testing
Annotated in YOLO format.



System Interface

Web-based interface

Precision: **0.865**	Recall: **0.824**
mAP@.50: 0.875	**mAP@.5.0.95: 0.64**

- YOLOv8Nano
- Unid GPU
- NVIDIA GPU
- Mosaic Augment

Severity Classification

- ✓ Real-time detection with YOLOv8
- ✓ Skeletonization of crack length
- ✓ Orthogonal crack width measurement

Severity Classification

Minor	Length < 100px	Width < 1.5 px
Moderate	100-200 px	1.5 – 3 px
Severe	>200 px	>7.8 pixels

Performance Results

- ✓ Real-time detection with YOLOV8
- ✓ Skeletonization of crack length
- ✓ Orthogonal crack width measurement
- Downloadable analysis report

Authors: Minuga Karthik Kumar
Nelavanka Nikhitha Sree

Guides: Dr.R.Praveen Kumar
Dr.G.Nakkeeran

A Synarastic Machine Learning-Learning-Metahetuntic Approach

Smart Grid Economic Load Dispatch Optimization

Amrutha BS, Prakash, Mr. Chodagam Srinivas, Mr. Bsh. Shayeez Ahamed, Dr. S. Padma, Dr. A V Pavan Kumar,
Department of CSE - AI and ML, Madanapalle Institute of Technology & Science, Andhra Pradesh

COLUMN 1 – PROBLEM

Economic Lod Dispatch (ELD)

- Minimize fuel cost
- Meet load demand
- Satisfy operational constraints

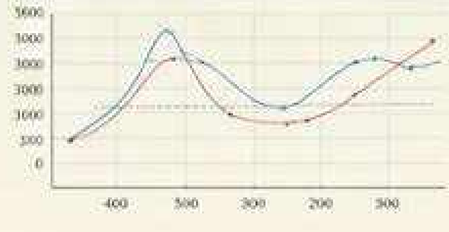
Why It's Challengied?

- Nolnaner cost curves
- Valve point effects
- Transmission losess
- Multiple local optima

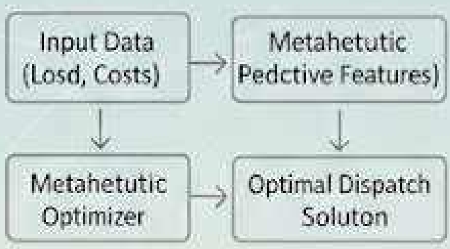
Test System

IEEE 30-Bus System
6 Thermal Generators
6 Thermal Generators
Load Cases: 200 MV | 283.4 MW | 320 MM

Non-corvex Production Cost curve



Hybrid Optimization Framework

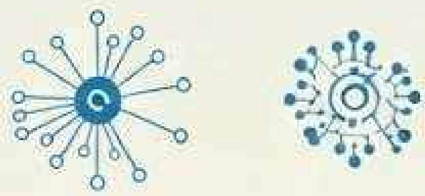


Machine Learning (ML)

- Data-driven insights
- Predict aat renwable outout
- Eaduce search space

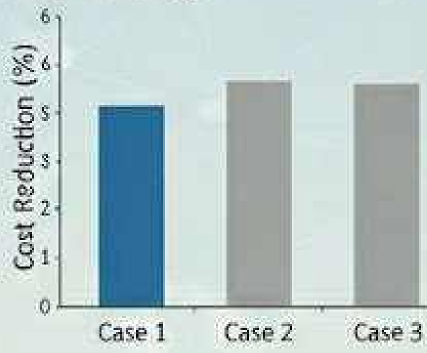
Metahetartic Algorithm

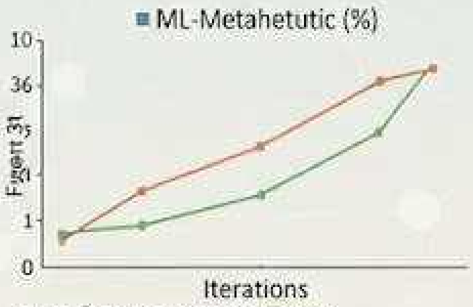
- Inspired by nature
- Explore diverse solutions
- Excape local optima
- Examples: PSO, GA, ALO



RESULTS & BENEFITS

Key Findings





Performance Boost

- 10-15% Fuel Coet Savings
- 20% Faster Convergence
- Enhanced Adaptability
- Improved Robustness

Societal Impact

- Greener Energy Efficiency
- Grid Reliability
- Sustainable Future

Predicting Concrete Compressive Strength Using Machine Learning

Dr. S. Padma, Dr. G. Nakkeeran
D. Venkat Nirmal Sai, S.TejaSree.
Department of Computer Science and Engineering
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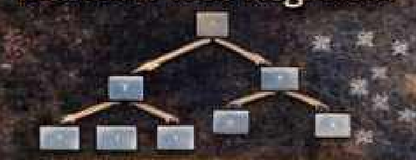
Objective

MACHINE LEARNING

- **Develop and compare ML models** to predict compressive strength of concrete based

MACHINE LEARNING ALGORITHMS

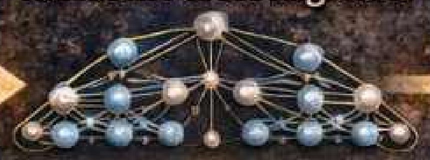
Decision Tree Regressor



$R^2 = 1.0000$ MSE=0

Perfect

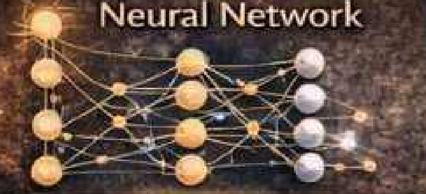
Random Forest Regressor



$R^2 = 0.9077$ MSE:0.0027

Good

Neural Network



$R^2 = 0.9902$ MSE:0.00830

Excellent

Performance Metrics:

$$MSE = \frac{1}{n}\sum (y_i - \tilde{y}_i)^2$$

- n = Number of data points.
- $\tilde{y}_i$ – Actual strength value.
- $\tilde{y}_i$ – Predicted strength value.

Coefficient of Determination:

$$R^2 = 1 - \frac{\sum S_{x2}}{\sum S_{tot}}$$

- $\sum S_{35}$ – Sum of squared errors
- $\sum S_{tot}$ = Total sum of squared differences from the mean

RESULTS

- ☑ All models effectively **predicted concrete strength** based on input features.
- ☑ **Decision Tree Regressor** → $R^2 = 1.0000$, MSE = 0.0000 (Perfect accuracy)
- ☑ **Neural Network** and **Random Forest** also showed high performance. $R^2 = 0.9902$, MSE: 0.00830
- ☑ Cement, **Fly Ash**, and **Dry Density** were key features influencing influencing compressive strength.

SMART TOURIST SAFETY & INCIDENT RESPONSE SYSTEM

AI + Geo-Fencing + Blockchain-Based Digital Identity

Department of CSE (AI & ML)

THE CHALLENGE IN MODERN TOURISM

- ✗ Unfamiliar surroundings
- ✗ Language barriers
- ✗ Delayed emergency response
- ✗ Fraud & iidentity misuse
- ✗ No real-time monitoring

SMART SAFETY ECOSYSTEM

AI Risk Detection
Real Time Behavior Analysis

Geo-Fencing Monitoring
Location-Based SOS Alerts

Blockchain Digital ID
Tamper-Proof Authentication

One-Tap SOS
Instant Access to Police & Healthcare

SYSTEM ARCHITECTURE

Proactive Detection → Automated Response → Secure Identity Verification

KEY INNOVATIONS

- Proactive Risk Prediction
- Auto-SOS Trigger
- Multilingual AI Guide
- Gamified Safety Reporting
- Tamper-Proof Digital ID

SYSTEM ARCHITECTURE

- Tensorflow / PyTordh (LSTM)
- Ehereum Blockchain
- NLP Chatbot (Multilingual)
- Real-Time GIS
- Ethereum Blockchain
- Cloud Architecture

IMPACT ON TOURISM

- Increased Tourist Confidence
- Economic Growth
- Reduced Crime Rate
- Safer Destinations

IMPLEMENTATION ROADMAP

- ✓ Phased Pilot Rollout
- ✓ Government Partnerships
- ✓ End-to-End Encryction
- ✓ First Responder Training

Guide: Dr. S Padma

Team Members:
M. Mohan Krishna
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T. Shanmuka Sai
K. Vardhan Kumar Reddy

Trensforming Travel Safety Through AI. Blockchain & Intelligent Monitoring

Load Frequency Control in a Two-Area Power System

using AVO-Optimized PID

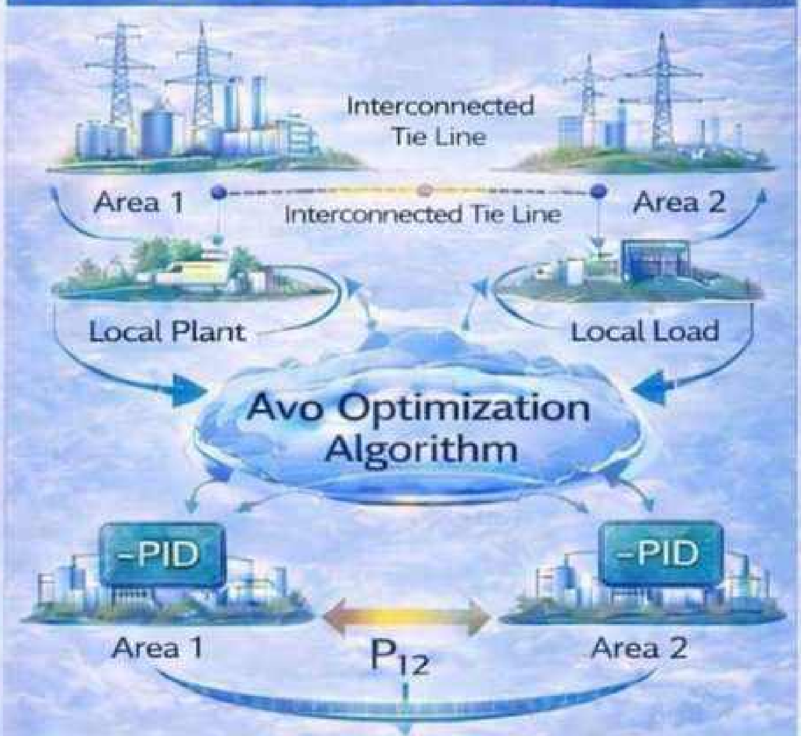
Dr. S.Padma, Dr. Praveen Kumar Rayani, Mr.Chodagam Srinivas,
P Yashaswini, Shaik Shagufftha

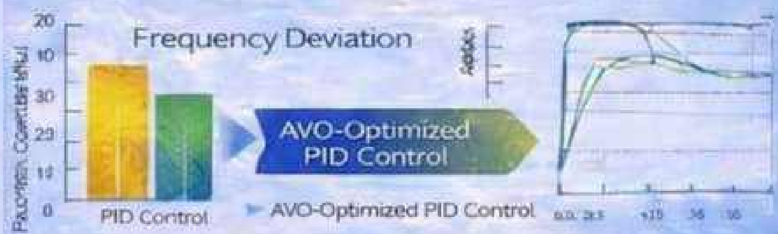
MOTIVATION

- Maintaining load frequency is crucial for the stability and reliability of power gnds
- Two-area power systems need coordinated control to maintain frequency balance
- Optimal PID (Proportional-integral-Derivative) control is essential for effective load frequency regulation.

Can an intelligent optimization technique improve PID-based Load Frequency Control in a Two-Area Power System?

PROPOSED METHOD





⬇ Settling Time ⬇ Improved

Improved Dynamic Stability

PERFORMANCE COMPARISON

Conventional PID	AVO-PID
Settting Time	Reduced Settting Time
Overshoot	Minimal Overshoot
Osciliations	Present Damped
Stability	Moderate Improved

ACHIEVEMENTS

- ✔ Improved Frequency Regulation
- ✔ Reduced Overshoot and Settting Time
- ✔ Enhanced Stability and Efficiency

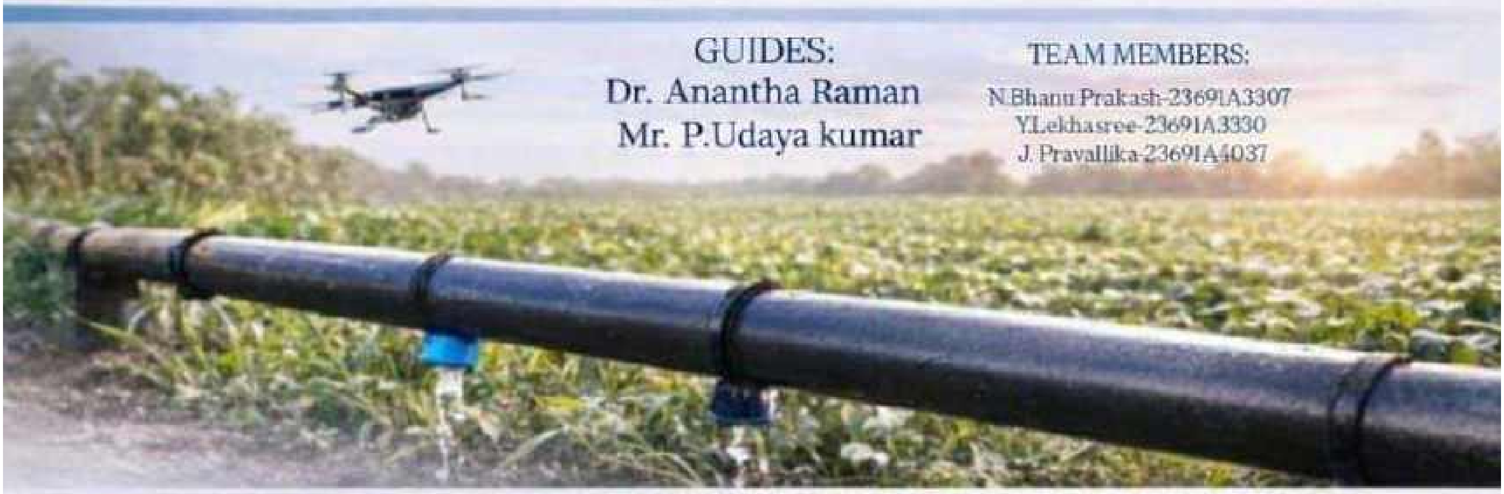
CONCLUSION

- ✔ AVO effectively optimizes PID parameters
- ✔ Significant improvement ever conventional tuning.
- ✔ Sutable for modern interconnected power systems
- ✔ Enhances grid reliability and robustness

FUTURE SCOPE

- Mullii-area power systems
- Integration with renewable energy sources
- Hybrid AI optimization techniques
- Real-time hardware implementation

AI-Driven Fault Detection and Prediction of Pore Blockages in Drip Irrigation Systems



GUIDES:
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PROBLEM

- Manual Inspection of Drip Lines
- Time-Consuming & Labor-Intensive Monitoring
- Undetected Pore Blockages Reduce Water Efficiency
- Uneven Water Distribution to Crops
- Yield Loss Due to Delayed Fault Detection
- Difficult Monitoring in Large Agricultural Fields

SOLUTION

- AI-Driven Automated Fault Detection
- CNN-Based Deep Learning Model
- Blockage Identification using Image Classification
- Predictive Analysis of Future Pore Blockages
- Real-Time Monitoring & Alerts
- Improved Irrigation Efficiency

TECHNOLOGY

Dataset > Preprocessing > CNN Model > Fault Detection > Prediction > Visualization

Python > TensorFlow / PyTorch OpenCV NumPy & Mattplolib

RESULTS

- High Fault Detection Accuracy
- Early Prediction of Pore Blockages
- Reduced Water Wastage
- Improved Crop Health Monitoring
- Reduced Maintenance Cost
- Increased Irrigation Efficiency

Smart AI for **Sustainable** Agriculture

AI-Based Crack Detection

R. BHAVANA (Roll No: 23691A3309)

Guides: **Dr. S. Padma, Dr. G.Nakkeeran**

PROBLEM

- Manual Crack Inspection
- Time-Consuming & Labor-Intensive
- Human Error-Prone
- Difficult for Large-Scale Monitoring
- Lack of Early Damage Detection

SOLUTION

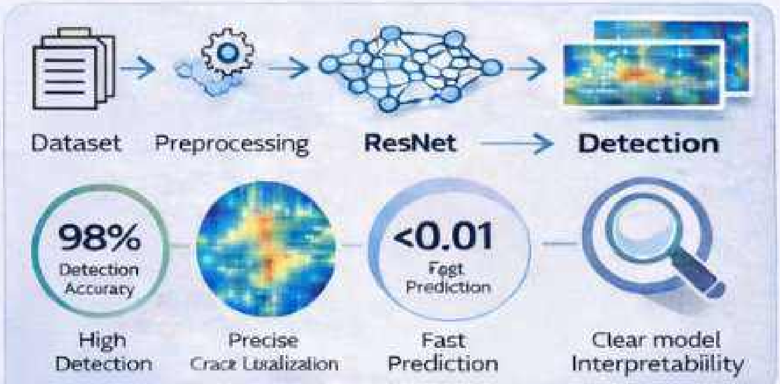
- AI-Based Automated Crack Detection
- ResNet Deep Learning Model
- Crack Localization using Bounding Boxes
- Model Explainability with Grad-CAM
- Fast & Accurate Real-Time Prediction

TECHNOLOGY

- Deep Learning (CNN)
- ResNet Architecture
- Bounding Box Detection
- Grad-CAM Visualization

PyTorch

OpenCV



RESULTS

- High Detection Accuracy
- Precise Crack Localization
- Clear Model **Interpretability**
- Reduced Inspection Time
- Improved Monitoring Efficiency

Characterizing Small-Scale Deforestation Trends in the NE Brazilian Amazon (2015–2025)

Dr. S. Padma[1], Dr. Nakkeeran G[1,2], Dr. Dipankar Roy[2], K. Vineesha[1], S. Lakshmi Sagar[1], Mrs. N. Geethanjali[1]*

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LANDSAT TIME SERIES ANALYSIS

THE FORGOTTEN NORTH

While the Southern Amazon's "Arc of Deforestation" is well documented, the **Northeastern Brazilian Amazon** (2.4 million km² spanning Roraima, Amapá, and Pará) remains critically understudied.
This region is unique due to its high percentage of **Indigenous territories (35-40%)** and protected areas.

> *"Is the NE Amazon experiencing systematic deforestation, or are forest dynamics primarily driven by climate variability?"*

METHODOLOGY

Data Source	Timeline
Landsat 8 & 9 OLI	11 Years (2015-2025)

We utilized **Google Earth Engine** to process annual composites of Surface Reflectance data.

- **Metric:** NDVI (Normalized Difference Vegetation Index).
- **Analysis:** Pixel-by-pixel Linear Regression.
- **Change Detection:** Year-over-Year differencing.
- **Cloud Masking:** QA_PIXEL > 20% excluded.

SPATIAL PATTERNS

Unlike the South, the NE Amazon shows no systematic "fronts" of clearing. The degradation is **patchy and scattered**.

Balanced Pixel Distribution: 49.6% Declining vs 50.0% Growing

TEMPORAL DYNAMICS

Linear regression analysis reveals **no statistically significant deforestation trend** (p=0.449). The variability is driven by climate events, specifically the 2015/2016 and 2020 El Niño droughts.

Figure 1: Mean Annual NDVI (2015-2025) showing climate-driven variability rather than linear decline.

5.78%
AREA WITH PERSISTENT DECLINE

-0.0002
SLOPE (NON-SIGNIFICANT)

0.065
R^2 VALUE (WEAK TREND)

~160k
AFFECTED AREA (KM²)

CONCLUSIONS

- ✓ **No Systematic Deforestation:** The NE Amazon is not following the path of the Southern "Arc".
- ✓ **Climate Resilience:** Forest health is driven by inter-annual climate variability, not land conversion.
- ✓ **Conservation Success:** Indigenous territories (40% of region) are effectively preventing large-scale clearing.

Recommendation:
Conservation policies should pivot from strict deforestation prevention to **climate resilience monitoring** and supporting indigenous land tenure.

SMART SAFETY SYSTEM

Detecting Harmful Gases in the Drainage System Using Gas Sensors

Project Overview

Drainage and sewer systems contain dangerous toxic gases that can cause serious health hazards and even death.

This project develops a **REAL-TIME GAS DETECTION AND ALERT SYSTEM** to ensure worker safety.

Guide: **Dr. S Padma, Dr.G Nakkeeran**

Team Members: **K Vardhan Kumar Reddy, G Navya**

Objective

- Detect harmful gases in drainage systems
- Monitor gas concentration continuously
- Improve instant safety when gas exceeds safe limits to ensure worker safety.

Gases Detected

- **Methane** (CH_4)
- **Carbon Monoxide** (CO)

LCD Display — Shows gas levels

- **Buzzer** — Emergency Alert
- **IoT Module** Remote monitoring

Features

- **Real-time** Monitoring
- **Automatic Alert System**
- Low-cost and Efficient
- Easy installation
- **Remote Data** Access

System Components

- **Microcontroller** – Arduino / ESP32
- **Gas Sensors** – MQ2 / MQ7 / MQ135
- **LCD Display** – Shows gas levels
- **Buzzer** – Emergency alert
- **IoT Module** – Remote monitoring
- **Power Supply**

Working Principle

- Gas sensor detects harmful gases in drainage
- Sends data to microcontroller
- Microcontroller shows gas value on **LCD**
- If gas level exceeds limit, it will:
  - **Alarm Activated:**
  - **Notification Sent**
  - **Warning Displayed**

Applications

- **Municipal** drainage systems
- **Sewage** treatment plants
- Underground pipelines
- Industrial waste management.