Vegetation Measurement Along the Line Corridor Using Satellite Imagery

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ABSTRACT

The project is an initiative to monitor trees using machine learning and smart technology. It works by analyzing images of vegetation to detect trees and sends alerts when the need arises. A large dataset of images of vegetation is used to train the system, which takes a powerful deep learning model known for its accuracy in recognizing objects in images, known as ResNet. In this way, it can accurately identify trees by distinguishing them from other plants.

Besides identifying trees, the system employs Internet of Things technology and monitors parameters such as height and exact location with latitude and longitude coordinates. The synergistic treatment of artificial intelligence with real-time monitoring helps the associated system efficiently track and map trees as they grow and change over time.

If the system detects something significant-like a tree that is becoming unsafe with a height that's gone high beyond a certain threshold-it automatically sends an email alert to the appropriate authorities. The alerts describe exact location details so that action can be taken without delay.

By integrating advanced image recognition and smart monitoring together, this system helps in tree tracking, promoting environmental safety and further supporting better forest management.

Index Terms— Measurement techniques, red edge, Vegetation Indices, ResNet Algorithm, Machine Learning, Satellite images, Artificial Intelligence, Line Corridor.

INTRODUCTION

It uses machine learning with IoT technology to effectively monitor tree health and provide solutions for effective care. Trees are vital for the restoration of balance in the ecosystem, community development, and conservation of biodiversity; these greatly aid in the monitoring and care of growth. Features are cropped from this image of vegetation, which help to distinguish one tree from the other, along with other characteristics like height and danger. The mother branch is based on the ResNet model, which is a cutting-edge deep learning algorithm suitable for tree recognition in any environment.

This system is unique among others because it really goes real-time by utilizing IoT. Using GPS modules and environmental sensors, this system needs to be tracked regarding the height and whereabouts of such trees by latitude-longitude coordinates. Whenever there is a serious incident; for example, if the height of the tree is beyond the set range, which can lead to its dropping, then the system issues a warning via email to mobilize any concerned parties to take precautions as soon as possible. Alerts are critical in tree care, environment protection, and urban planning.

It combines the real-time tracking with the AI-based image recognition to give the users a simple, elegant, and scalable tool for tracking trees. It helps to prevent continued manual evaluation that enhances the efficiency by which environmental matters are dealt with. It should facilitate tree monitoring and thus enhance the ease, accuracy, and rapidity of response by lenders, researchers, and urban planners.

LITERATURE SURVEY

Xuhui Zou, Yong Xie, Qifei Han, Wen Shao. (2024) explored a “Adaptation Analysis of Measurement Techniques and Inversion Algorithms for Tea Tree LAI” which proposed two commonly used measurement methods for densely and sparsely grown row crops and a measurement method for densely grown tea trees proposed based on practice, three sets of tea tree LAI were measured and compared with the true LAI value obtained using direct measurements. Using the set with the best performance to construct a regression model with vegetation indices, the LAI during the new shoot period of tea leaves is inverted.

Jie Li, Dongkai Yang, Feng Wang. (2023) presented a “A New Algorithm for Measuring Vegetation Growth Using GNSS Interferometric Reflectometry” which explored a calibration model that can reduce the influence of SM and snow layer on reflectivity. They used a direct-reflected signal amplitude ratio and GNSS-IR altimeter based on the Lomb–Scargle Periodogram to calculate the reflectivity of vegetation and snow layer depth. GNSS data from plate boundary observation were used to verify the validity of our model.

Glaucio L. Ramos, Nuno R. Leonor. (2024) discussed a polarimetric measurement campaign conducted in two distinct environments, with data collected at the Federal University of Minas Gerais (UFMG) in Brazil. The study investigates millimeter wave propagation through vegetation at a frequency of 36.6 GHz in two scenarios: the Central Square of UFMG and a forested area within the

campus. In the first scenario, measurements were conducted along a main street with varying degrees of vegetation obstruction, focusing on analysing fast fading. For the fast-fading analysis, Rayleigh, Rice, and mNakagami distributions were considered.

Cheihping Lai, Damir Senic. (2023) their article presents an extensive literature review of state-of-the-art academic publications as well as commercial market offerings regarding the applicability of “Raytracing Digital Foliage at Millimeter-Wave: A Case Study on Calibration Against 60-GHz Channel Measurements on Summer and Winter Trees”.

Andreia S. Santos, Lucas Teles Faria. (2024) porposed a “Estimation of Vulnerable Areas to Faults Caused by Tree Vegetation in Power Distribution Systems” which utilized an enhanced method for tree vegetation mapping by areas is developed using multilayer perceptron neural networks trained on high-resolution images from Google Earth. A geographic space is incorporated to estimate the regions vulnerable to failures due to tree vegetation. Geographically weighted spatial analysis is applied from local variables aggregated by areas. Spatial data analysis is used to real faults and tree vegetation data from a medium-sized Brazilian city via QGIS and R programming environments.

Proposed System

The proposed is an automatic tree detection and alert generation from vegetation images using an innovative machine-learning-based solution. This identification and classification of trees in different vegetation covers from putative images are done with the aid of the ResNet algorithm, a deep-learning model well known for its high accuracy and effectiveness in the field of image recognition. Trained on various datasets, ResNet has shown reliable performance in the detection of trees in different growth stages over various geographic settings.

With it comes the advent of such versatility that can be derived from the IoT systems. This system will not just identify a tree but will also pinpoint coordinates if that tree happens to be of a particular danger after a specific height. The provided coordinates will be included in real-time alert messages to the forest officials, urban planners, and environmentalists. This information will be played before them and will allow prompt action in case of tree maintenance, environmental safety, and urban planning.

The combination of the ResNet algorithm for exacting detection and IoT for tracking geospatial information will thus make the system a very effective tool for contemporary environmental management. The fact that it combines both approaches in the real-time and the more long-term provides enabling actions as decisions that can therefore serve better to notify.

Key benefits:

1. While reducing human monitoring, trees can be identified easily with the aid of this tool, saving time and effort in large vegetation areas.
2. Allows identification and real-time alerts for immediate action and decision-making processes for critical tree species.
3. Is capable of processing large amounts of data and adapting to different regions, thus enabling the monitoring of different vegetation types in different environmental contents.

Implementation

Implementation of the machine learning based Vegetation Measurement Along the Line Corridor Using Satellite Imagery system proceeds by following a well-structured pipeline:

i) Data Collection and Data preprocessing

Data collection and preprocessing is the initial phase of our implementation which includes gathering high-resolution satellite imagery for line corridors from specific satellite providers.

ii) Feature Extraction

Principal Component Analysis (PCA): Dimensionality reduction, retaining the salient features that distinguish the satellite images before and after.

Feature Importance Analysis: Casting light on important features, such as sudden changes in vegetation structure and abnormal patterns in line corridors.

iii) Model Training

The model is trained using the technique of Convolution Neural Network (CNN) with the implementation of the Residual Network (ResNet) algorithm.

iv) Tree detection and Tree Classification

The trained model will be applied to satellite imagery for automated tree detection along the corridor.

Classify the trees by stage of growth, height, and potential threats; for instance, power line encroachment or restricted area encroachment.

v)IoT implementation

A major part of that is to harness the power of Internet of Things technology mechanism to detect trees and alert system which will facilitate the real time monitoring and data transmission. These devices record accurate readings of tree height, environmental conditions, and geographic
location — latitude & longitude coordinates

vi) Alert Notification

Through the Notification Module of the proposed system, real-time alerts. This module establishes an automatic mechanism of alerts that notifies if a tree is at a critical height or threatens something.

Incorporated with the email or SMS services to get notified to the relevant authorities like the forestry department or urban planners to act in time.

vii) Testing and Deployment

The trained model may be deployed on a cloud-based platform and/or edge devices that allow vegetation monitoring on continual bases. Implement real-time updates that can be monitored by stakeholders for dissemination on a web dashboard or mobile application about tree growth and risk assessments.

viii) Scaling and Support

Regularly evaluate the tree detection and alert generation performance by comparing model predictions to reference ground data.This enables improvements to the system through new satellite data sources, algorithm refinement, and better user feedback in terms of efficiency and reliability.

5.System Architecture

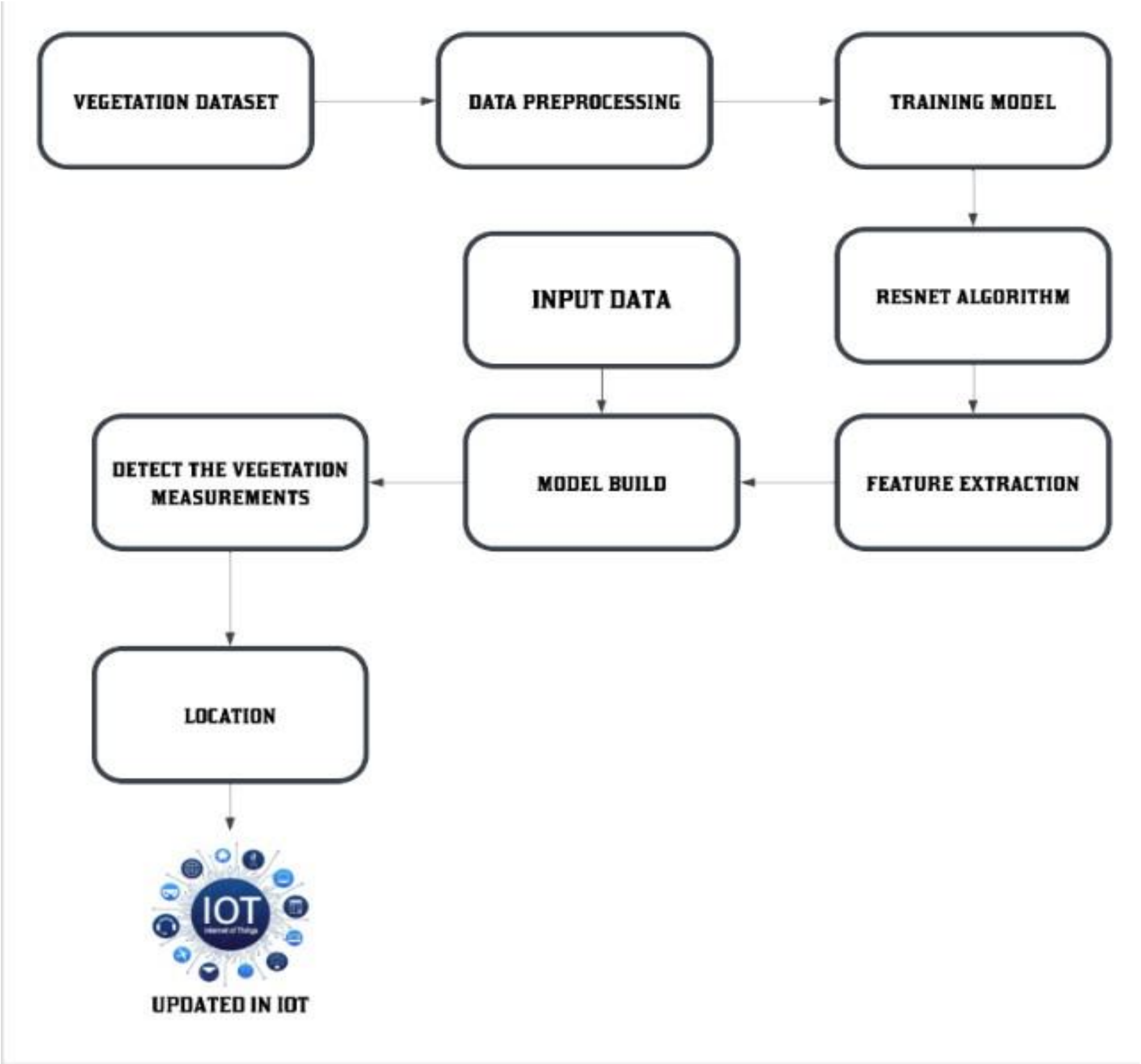

FIG.NO 5.1

The system under development is intended to use machine learning and IoT integration techniques for building the app that tracks the tree and plant vegetation across the line corridors. The system is integrated with the notification alert system which notifies the users whenever there is a suspicious or rapid changes in vegetation. The architecture consists of three main components: Frontend, Backend, and Deployment

i)The frontend of the web environment

Involved HTML, CSS, and Angular to create a responsive interface. The web application is a map-based application which makes use of the GIS technology, which allows the user to view and tree height and abnormal changes in pattern of the vegetation.

Pass input data to the backend via a REST API for to store in blocks in a chained network.

ii) Backend

Built on Flask, which is a light web framework for Python. Performs the role of serving API requests, processing input data, and communicating with the all the modules such as image processing module, IoT integration module, 6G intelligent module and the user interface module.

ResNet Algorithm: OpenCV with TensorFlow/Keras for deep learning-based biometric authentication.

iii)Model development

For model development and comparative analysis, the dataset is divided into Training Set and Testing Set.

Three models (Decision Tree, Random Forest, and Logistic Regression) are trained and compared.

ROC Curve and AUC Score-The ability of the model to differentiate between past vegetation image vs the present vegetation image.

Measures of stays of performance, and precision-recall-f1 score.

Computational efficiency in the real time deal.

The best-performing model in terms of performance metrics being utilized in developing web services to run the fraud prediction algorithm was chosen and installed with Flask for integration.

iv)Deployment

The model-trainer is saved using Pickle (PKL) or Joblib for later implementation in the API.

Flask provides the RESTful API that serves real-time SMS data and returns predictions for fraud

RESULTS AND DISCUSSIONS

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FIG.NO 6.1

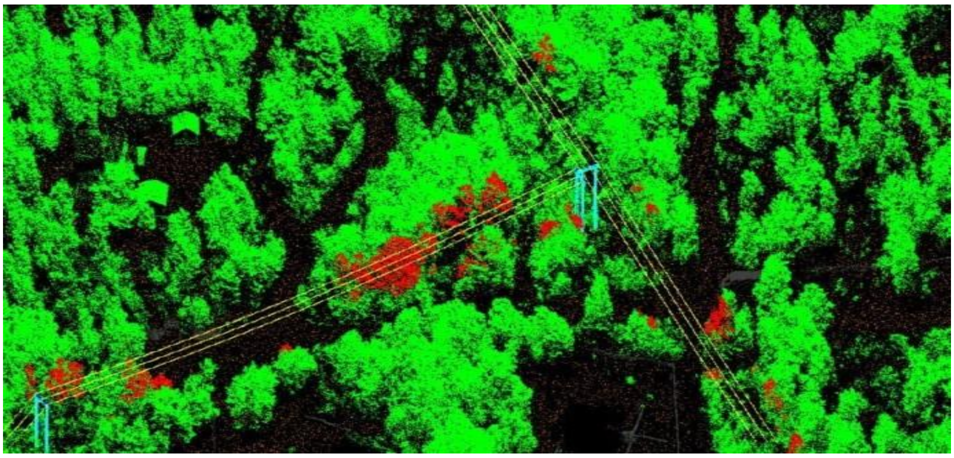

FIG.NO 6.2

Fig 6.1 and Fig 6.2 is the satellite which the machine learning model continuously monitors, tracks and detect changes. The images can also be viewed by the user through the user interface.

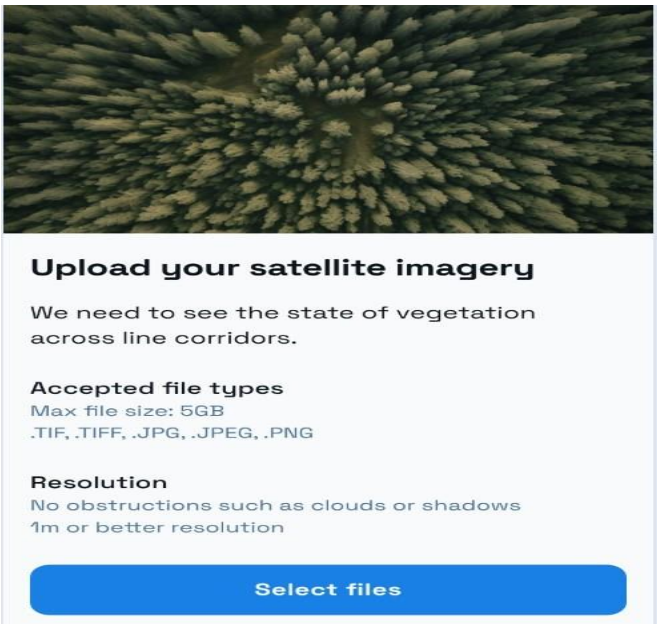

FIG.NO 6.3

The above Fig No 6.3 depicts the user interface which asks the user to upload the satellite imagery and detects the changes in the vegetation across the line corridor.

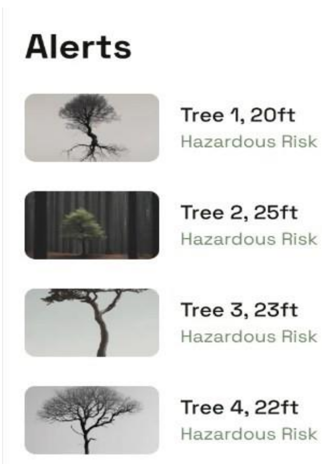

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FIG.NO 6.4

FIG.NO 6.5

Fig 6.4 and Fig 6.5 are the notification alert system which notifies the user whenever there is a abnormal change in the vegetation across the line corridor.

Future Enhancement

The next version of the app can be decidedly more accurate, efficient, and user-empowering. Advanced artificial intelligence models-such as EfficientNet or Vision Transformers-should perform even better when dealing with trees growing in varying environments. Applications of multispectral imaging could treat various tree ailments and monitor the overall health of the tree. Loading would be increased as a function of a wide variety of images of vegetation.

The system could incorporate edge computing, enabling it to perform all data processing on small devices, such as Raspberry Pi, thus achieving higher performance and speed without connecting it to cloud servers. Drones supporting LiDAR would be used to scan large geographical areas and to provide accurate height and density measurements of the trees. The system would support a mobile application that would help users view real-time data, log personal observations, and notify them.

These IoT sensors could generate data on soil moisture, air quality, and temperature, thus providing an overview of tree health. Blockchain provides that data in an auditable and reliable manner. Community involvement could go further and improve the system by allowing public contributions and sharing of tree data. And then, an AI-based alerting system would be able to prioritize things on its own, which in turn would facilitate an expeditious response by the responsible personnel. These enhancements will make tree monitoring smarter, more responsive, and operationally simple for the entire world.

CONCLUSION

The smart tree-keeping mechanism creates the modern next-generation paradigm for trunk monitoring, with highly specialized ways supported by deep-tech capabilities from the field of machine learning. The ResNet AI model calls attention to trees in photos, thereby fast-tracking the modernization, so you need not engage in a constant eye-popping exercise. The system has been found effective in forest management, urban planning, and environmental protection. In addition, it will send out instant alerts through SMS and email for rapid response in case of emergencies.

These IoT systems will provide information about monitoring tree height and certain important parameters, and real-time updates will always be coming in. Future developments may include drone observation, most modern sensors, and participation from the local community; each of these is likely to further increase the efficacy of this project. It places itself in advocacy for tree detection and monitoring automation toward sustainable environmental efforts and wise decision-making. Inevitably, it sets the train that leads to green cities, healthy forests, and some ways to conserve the earth for the great benefit of generations to come.

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