Tree-level identification and classification leveraging image data analysis

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FINAL YEAR DESIGN PROJECT REPORT

This Report Presented in Partial Fulfillment of the Requirements for the **Degree of Bachelor of Science in Computer Science and Engineering**

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APPROVAL

This Project titled " **Tree-level identification and Classification leveraging image data analysis** ", submitted by Name : **Sadman Sakib Roktim** ID : **211-15-14672** to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on **17 September, 2025**.

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We hereby declare that this project has been done by us under the supervision of **Mr. Raja Tariqul Hasan Tusher, Assistant Professor**, Department of Computer Science and Engineering, Daffodil International University. We also declare that neither this project any part of this project has been submitted elsewhere for the award of any degree or diploma.

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ABSTRACT

The environmental monitoring, agriculture and forestry management depend on the categorization of trees like fruit, medicinal or forest tree. The aim of this project is to develop a trustworthy deep learning system to recognise these classifications of trees based upon images of their leaves and bark. Thus three DNN architectures were used: ResNet50, ResNet101 and InceptionV3. The dataset used for training and testing included a diverse set of images taken from different sources, and showing different species of trees in different environments. These images were preprocessed, resized, normalized and augmented so as to ensure that the models can learn and generalize effectively. They are transfer learned using pre-trained ImageNet weights for the three models. We evaluated the models based on performance metrics (accuracy and loss) on both training and test sets. The ResNet101 is only one of the 3 models trained with a maximum test accuracy of 85%. ResNet50 and InceptionV3 produced similar results with slightly lower accuracy. This result also gives an evidence to indicate that the deep's ability of deeply structure such as ResNet101 on merging the complex characteristics and patterns over leaf and bark images for tree classification. The results in this paper can provide basis for practical applications of automatic tree identification, e.g., forest management and ecologic studies. In the future, the methodology and research can be expanded by involving a larger data set and multiple models to enhance both accuracy and scalability.

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Chapter 1

Introduction

1.1 Introduction

Correct determination of the tree species is important in many fields, including forestry, ecology and conservation. Tree identification is a fundamental step in biodiversity assessment, habitat management and ecological studies and also provide the necessary background for monitoring and for promoting sustainable forest management. However, to distinguish trees is difficult due to different shapes in tree of the same and a different species, natural environmental variety also known as phenotypic variation and similar species. All these problems become worse in larger ecosystems where changes of images by light, angle of viewing and season can have major consequences on accuracy [1].

Tree species identification, regardless if by manual or digital means, has always been difficult. Manual annotation relies on experts' knowledge that results in low-efficiency and accuracy. Digital solutions are faster, but they often have to be heavily engineered and rely on the input data quality. The popularity of citizen science platforms such as iNaturalist further complicates the picture. Although such datasets are useful, and to the best of our knowledge there is no currently available dataset offering chest thermal images along with labels for Covid-19 detection, filtering the collected low-quality image sequences taken by non-experts might decrease the efficacy of training data and making constructing feasible classification models is really challenging.

In this study, we present an approach for large tree species recognition via image processing and deep learning. To be more precise, we use convolu-tional neural networks (CNNs) that are very good at recogniziing patterns and extracting image features hierarchically. It is worth noting that, in a prior study by Mohanty et al. (2016) and Carpentier et al. (2018) has shown that the CNN-based models can be effective for plant and tree classification on challenging databases.

We augment these methods by using novel techniques like cluster-based supervision, label correction and data augmentation to reduce the effects of noisy training labels and enhance the quality and reliability of our dataset.

A strong and true tree identification method contributes to not only better the classification accuracy, but also more robust models. The system could potentially be used for ecosystem surveillance, tree species diversity awareness and to add to invigorating the ecosystem. More generally, the approach provides scalable and automatic tools that can support biodiversity monitoring and sustainable forest management underpinning conservation actions in a practical and applicable way.

1.2 Motivation

Ecosystems are under growing threat from urbanisation, deforestation and climate change, which gives added urgency to the monitoring and conservation of tree species. Correct tree species identification and organ ontogeny identification are basic novel elements for good ecosystems management, but current morphological or molecular methods are slow, expensive and depend on expert knowledge. This proposal will overcome these limitations by providing the technological framework to process images and automatically classify tree species.

Such a system is generally applicable. It allows scientists, educators, ecologists, policy-makers and conservationists to classify trees quickly, accurately and cheaply. The reduction of the dependence on human subjective observation not only improves operational efficiency in forestry management, urban planning and biodiversity studies. Especially when evaluating forest health, invasive species and environmental change, knowing the specific species is crucial; it provides policymakers with information required to make sound conservation decisions, while researchers can better understand species' distribution/inter-relationship.

Beyond the use of scientific and policy applications, the project raises public awareness and involvement in tree diversity. By providing user-friendly interfaces (like on a mobile app or web-based) people who may not be research scientists can contribute to data collection and conservation. In this regard, technology is a bridge between people and the natural world which, in turn, enables them to engage themselves with ecosystem stewardship. At its core, this effort shows that combining technological innovation with ecological sensitivity can help to solve the decline in biodiversity and promote a sustainable environment in which future generations can succeed.

1.3 Objectives

The project will generate main goals for addressing these issues and make a second important contribution to environmental science and computer vision related to tree species identification. These goals include:

or from the leaf or bark of a tree 1 INTRODUCTION The task is to develop a robust image processing algorithm for an automatic detection and classification of different tree species. It will exploit the best technologies (to be sure results are robust and generalize across environments and to differences in species) with algorithms (CNNs, VP of brains).

Building a user-friendly interface: The interface will be to build an interface through which the user (either researcher, environmentalist and policymaker) can upload the image and get the result of tree identification. So that non-techies have access to interface, to make it available in many platform.

Assessing system performance :This is one of the main objectives of project is to extensively compare the performance the new system against a standard tree identification systems The judgment for its effectiveness will happen based on its accuracy, precision, recall and computational efficiencyComparative study between the proposed system and existing manual methods and other automated approaches can and should be performed to further refine the boundaries and also to validate the robustness of the techniques.

Targeted Contribution to Environmental Science

Also, this work is another original contribution to the community between environmental science and computer vision. The implementation challenges faced such as this species being quite similar to other species, background noise that naturally grows in the vegetation used and data mismatches due to the dataset being mislabelled and then fed into training. The approaches, results and insights produced will probably inform future biodiversity monitoring and machine learning applications to ecological research.

These goals are positivistic at little, but are thus a natter of the larger pattern of using innovation to improve the humancomprehension and control of the natural world; hence the loose presence of a feasible way of life with the natural world–a face (editorially) showdown between computer vision and ecological science.

1.4 Methodology

The insight driven from these considerations is that design of a full fledged system which can automatically recognize with high confidence the tree species should be organized. The methodology is suitable for the entire project lifecycle – from explorative research to practical application in real world -, and emphasises model validity, robustness performance and user-in-the-loop experience.

Literature review: The first stage is to review the literature that deals with conventional as well as recent approaches for tree identification, image processing, CNNs and transfer learning models. Finally, the discussions in this review indicate that there are several new directions for future investigations to be explored and provide a foundation for novel contributions in the current study.

Data Collection and Preprocessing: A diverse set of tree images is gathered, focusing on the leaves and trunk/bark as key components. Images are gathered from public repositories, citizen science initiatives and field campaigns. Pre-processing including resizing, normalization and data augmentation are conducted to enhance the quality of training set for better generalization and less sensitive to environment change.

Model training and testing: Various image processing techniques would be studied for feature extraction to improve the performance of classification. We will train the popular CNN pretrained models such as ResNet101 and InceptionV3 on our processed dataset for finetuning their layers to improve the accuracy. Transfer learning will also be used to enhance the model's performance, particularly useful in cases where there are a small number of labeled examples.

Model training/optimization: The model will be trained on the training dataset using iterative procedures to minimize loss and increase performance metrics such as accuracy, precision, and recall. Regularization techniques such as dropout and data augmentation will be used to prevent overfitting. The models for classifying tree species will be further tuned through hyperparameter tuning.

System Integration and Interface. The developed model will be integrated into a Graphical User Interface (GUI)System to make it user-friendly. This interface will allow the user to upload a tree picture and receive a result of what the tree is. The system will be user-friendly so that researchers, environmentalists, and the public in general can use it.

Evaluation and testing: The system will be tested and evaluated and will solicit user-feedback to be tested on unseen data. Performance metrics (validation accuracy, training loss, confusion matrix) will be examined for reliability. End-user (like researcher, conservationist) feedbacks will help to further improve the system functionality and usability.

Deployment and Scalability: Upon completion of evaluation, the system will be initialized for deployment, for possible application in ecological research, forestry management and education. The design will be scalable to include the possibility of new features, for example to identify the health of tree or by season.

Documentation and Reporting: A report documenting the method, results and system design will be developed. This work will be a key resource for future research and development in tree species identification and related fields.

Through following this systematic process, the work aim to devise a reliable, accurate and user-friendly tool that makes a significant contribution to the conservation of ecology and biodiversity studies.

1.5 Project Outcome

With a good tree identification system in place we can recognize species from images and achieve better performance. This fact renders the project of special value for ecological and biodiversity studies. Our aim is for this system to be low-cost, distributed and capable of running complex image processing and deep learning algorithms. Still, challenges remain. The job of the managing large amounts of data and making public the resulting data are what will stand in the way, which could take another year to resolve — with a two-year out final report.

Apart from its immediate goals, this study is a useful reference work for the purpose of subsequent research. It can give a sense, however, to readers who are curious how machine learning could be used for ecology in practice; it may also help those who would like to build an even more sophisticated tree identi cation system.

The societal relevance of this project may be very wide. It will be a weight off my shoulders to have trees detected automatically (an issue for us all as environmental managers, especially in the forestry industry where discussion of invasive species can grind progress to a halt). Waters sees potential

1.6 Organization of the Report

This file is organized in several parts, one for each aspect of the tree species identification. The order of these chapters is structured to walk the reader through the project's methodology, implementation, results, and significance.

Chapter 1: Introduction

The project's theoretical frame and motivation are introduced in the introductory chapter, highlighting the importance of identifying trees for ecological research and conservation efforts. It also describes the objectives, approaches, and results of the project. A description of the organization of the report is provided at the end of the chapter.

Chapter 2: Background

This chapter offers a comprehensive review of the available literature and research regarding tree species identification, image processing, and deep learning. It highlights shortcomings in current methodologies and discusses analogous applications in related domains. This chapter establishes the context for the project and underscores the necessity for a more automated and precise identification system.

Chapter 3: Research Methodology

Details the research methodology employed in the project, outlining system design, data collection, and the various tools and techniques used. It addresses both the functional and non-functional system requirements, the process of selecting models, and the overall workflow of the project. Diagrams and flowcharts are included to demonstrate the system architecture and procedures.

Chapter 4: Implementation and Results

This chapter elaborates on the system's implementation, covering environment configuration, data preprocessing, and model training. It examines the performance of various models (ResNet50, ResNet101, InceptionV3) based on testing outcomes, discussing metrics such as accuracy, loss, and validation. A comprehensive examination of the findings is provided, comparing the efficacy of the models.

Chapter 5:Communication Standards and Design Challenges

Focuses on the engineering principles used to design and develop software, hardware, and communications. It also discusses some of the issues that we ran into during the project regarding the data quality, model optimization as well as the ethical considerations. This chapter considers the societal and environmental implications of the system in different potential applications.

Chapter 6: Conclusion

The final chapter summaries the main conclusions of the study, discusses its limitations and offers some recommendations for further research. It concludes by considering the impact of the project on the identification of tree species and discussing possible refinements and additional components of the system that could be developed.

This chapter-by-chapter approach results in a complete portrait of the overall project development, from the initial concept to the final product and its conclusions.

Chapter 2

Background

2.1 Introduction

During various ecological, forestry, and conservation projects, the precise recognition of individual trees is of great importance. It is important in monitoring and managing biodiversity, habitats, and the environment to help ensure sustainable management and conservation. Knowledge on tree species diversity is fundamental to monitor the effects of climate change, to measure the health status of forests, and to manage natural resources in a sustainable way. Traditional ways to differentiate wood types – based on physical characteristics like leaves, bark, and fruit – can be hindered by the similarities between species and variations of the climate and soil. For example shape or size difference in leaves can lead to misclassification, even by experts. Vijayashree and Gopal [1] drew attention the image processing has so much potential to meet these challenges, which was demonstrated by the enhanced accuracy in leaf-based plant identification.

Advances in technology, particularly machine-learning and image processing have revolutionized the classification of tree species. CNNs have been proven to be powerful tools in ecology research due to their pattern recognition power. Chaki and Parekh [2] showed that CNNs were able to use shape-based features like leaf morphology, edges and contours, to classify plants under various species. They address the complexities of visual recognition problems and give the standard solutions to realistic datasets. However, CNNs require large numbers of annotated images for training, which are not always easy to collect.

Launched to increase the accuracy of predictions on the misclassified image-side images that people may take in their daily lives, such platforms as iNaturalist and Leafsnap deliver many pictures of trees. But because its labels rely on non-experts, they often contain mistakes involving misuse of the term. Mislabelling an image in this manner can disrupt model performance as a whole, so producing even less accurate predictions. Valliammal and Geethalakshmi [3] probed this problem, and then applied hybrid systems the combination of classical image processing with machine learning to increase the recognition rate. They noted that the quality of their dataset was in need concern, proposed methodologies such as clustering and label correction in order that the dataset would grow better and more reliable while their model still functions normally. Moreover, by so doing they also found solutions for many technical problems to which we must attend. Feature extraction is another important step in improving accuracy. This means that for k machine learning models to perform more accurately, leaf shape, texture and color also prove important variables. And while Kaur and Kaur [4] pointed out the importance of integrating the three, so as to form a comprehensive database from which k models living within natural science could draw data, at no time did they tell us anything about what such a database should look like. Shape descriptors are found to be particularly helpful. For example, combining shape, texture and color features with CNNs enables the subjects of classification to be more accurately spotted wherever their ecological situation is found.

Yahiaoui et al. [5] found that this method increased the accuracy and reliability of classification across multiple ecological conditions. Kaur and Kaur [4] explained how transfer learning could be applied with maximum success: in transfer learning, one makes effective use of knowledge gained from general plant recognition for purposes such as improving sound classification. When necessary, the newly updated model can thereafter be reused by licensing your own work under an increasingly open license. Emerging together, these technologies imply that with the right CNNs, feature extraction and transfer learning, robust and scalable tree identifications systems will be forthcoming.

2.2 Literature Review

The identification of trees is a basic work in environmental science, forestry and conservation. Current approaches are based on the manual identification and may be difficult, time-consuming and erroneous. More recently, with the advent of Computer Vision and Deep Learning this operation may be automatically carried out obtaining more reliable and quick results.

Limitations of Traditional Methods

The tree species identification process is usually manually done based on its leaves shape, bark texture and branching patterns. These methods work very well in some instances but are heavily reliant on expert knowledge and intolerant to when species are similar, or environmental conditions differ. Vijayashree and Gopal(2015) introduced image processing methods for leaf based system with plant identification compared to manual system performance, it still need many feature extraction process as well as require basic pre-processing done manually.

Contribution Of Deep Learning in the Identification of Tree Species

The developments in deep learning, especially, CNNs have brought a breakthrough in image-based classification. Mohanty et al. (2016) attempted to apply CNN to plant disease recognition using leaf images in a crop and obtained good results, it became possible that CNN could be utilized in larger scales of ecological study. Similarly, Carpentier et al. (2018) applied CNNs to classification of bark image, and showed ability in modeling detail of texture or pattern peculiar to tree species.

CNNs have been more effective in ecological studies with transfer learning. By retraining pre-trained architectures such as ResNet and Inception, the authors achieved impressive speed-ups at training time whilst maintaining high accuracy. For example, Selda et al. (2017) applied SVCs and image processing in plant identification, and this application models the promise of machine learning for such classification tasks.

Data and label challenges

The main challenge of employing deep learning for tree species recognition is the paucity in data source quality. However, labels are metainformation and probably noisy, especially when originating form the wild, e.g. citizen science projects. The problem was also addressed by Valliammal & Geethalakshmi (2011) by using traditional image processing techniques combined with machine learning, in order to achieve better classification, assuming noisy data sets. Yahiaoui et al. (2012) highlighted the importance of feature extraction methods, i.e., descriptors for shape of the leaves, for the purpose of increasing the classification accuracy when dealing with complex objects.

The Convergence of Image Processing and Machine Learning

The integration of the image processing methods with machine learning has shown promising results to increase the classification accuracy. Chaki and Parekh (2011) also emphasized the strength of shape-based features along with CNNs in discriminating plant species, emphasizing the effectiveness of these methods while dealing with varied datasets. These two approaches guarantee more flexibility to the classification system to take into account different ecological contexts and species' features.

Looking Ahead

Although existing work has shown that CNNs and transfer learning are promising tools for tree species identification, scalable and user-friendly systems are still in demand. Further work may focus on real-time applications, including functionalities for the health condition of tree or seasonal change detection, and the utilization of mobile or edge devices in field-based applications.

Table 2.1: Summary of Literature Reviewed.

Author (s)	**Year**	**Title**	**Methodology**	**Key Findings**
Serdar Selim et al.[12]	2018	Semi-automatic Tree Detection from Images of Unmanned Aerial Vehicle Using Object-Based Image Analysis Method	Decision trees and SVMs	Probably obtained decision trees and SVMs are also efficient classifiers for identification of tree species from bark images when used in combination with 5 6 different feature subsets. convolutional neural
Mathieu Carpentier et al.[11]	2018	Tree Species Identification from Bark Images Using Convolutional Neural Networks	CNNs with transfer learning	Likely demonstrated that CNNs with transfer learning effectively enhance tree detection in images taken from unmanned aerial vehicles, leveraging object-based image analysis methods.
Jianping Fan et al.[13]	2015	Hierarchical Learning of Tree Classifiers for Large-Scale Plant Species Identification	Relied on manual feature extraction	A likely key finding is that hierarchical tree classifiers learning for plant species identification is effective but heavily relies on manual feature extraction, which may limit
Jesse Dave S. Selda et al.[14]	2017	Plant Identification By Image Processing of LeafVeins.	SVC(Support Vector Classifier)	Likely showed that support vector classifiers (SVCs) are successful for plant identification through image processing of leaf veins, by the reasons, by the importance of vein patterns
Z. Zhang, Y. Wei, and H. Li[6]	2019	Plant species identification using deep learning with large-scale leaf datasets	Convolutional Neural Networks (CNN)	Demonstrating the effectiveness of CNNs for handling complex and diverse ecological data.
I. Yahiaoui, O. Mzoughi, [5]	2012	Leaf shape descriptor for tree species identification	Convolutional Neural Networks (CNNs)	The paper demonstrates the effectiveness of a leaf shape descriptor for accurate tree species identification.
A. Kumar, P. Sharma[9]	2019	Edge-based detection and identification of tree species using aerial images	Support Vector Machines (SVMs)	Edge-based detection effectively identifies tree species using aerial images.

2.2.1 Similar Applications

The plant identification with image processing and computer vision has proven to be promising and efficient (Joly et al., 2014) indicating that it will likely also help in ecological studies. Comparable smart applications like PlantNet and LeafSnap also allow keyboard to recognize the species of plants from leaf images using advance algorithmic recognition technology along with convenient user-interface. PlantNet, for example, is applicable to the fine-level plant classification and has been extensively used in biodiversity monitoring. Similarly, LeafSnap combines computer vision to identify the species of trees based on photographs of their leaves crossing the simple identification tasks off of everyone's list (anyone from scientists and more specifically laypeople).

The applications on species recognition presented above have demonstrated the importance of CNN and transfer learning. CNNs are able to capture more complex visual leaf features e.g. shape, texture and venation based patterns that cannot be recorded using the traditional techniques. Mohanty et al. demonstrated with the visual plant network (VPN) that plant diseases can be accurately determined from leaf images and argued their wider use in identification of plants and trees.

Related to that is the rise of citizen science. Photo-sharing sites, including PlantNet and LeafSnap, actively encourage the upload of photographs (more is better — because who knows whether any given database provider can secure physical comparisons?) This not only provides valuable accelerating information for maintenance of biodiversity monitoring, but also elevates local public knowledge on plant diversity. Nevertheless, this non-expert participation has potential unwanted effects like misclassification or input of incorrect data which in turn could deteriorate the quality of the models (Valliammal and Geethalakshmi 2011).

However the successful outputs of these apps provide hope for utilizing image processing, computer vision and ecologance. In the future with further technology development, these will be more enabled systems that provide live species identification, tree health monitoring and link to GIS for spatial analysis. Together these progresses will greatly help in the ability to understand and preserve biodiversity and greenspace.

2.2.2 Related Research

Vision based systems are on the rise, in applications such as agriculture, ecology and biodiversity. This intuitive tools make it very fast to analyse massive data sets. In recent years, convolutional neural networks (CNNs) have been presented as the best performing approaches with respect to plant classification. In some researches, it has been shown that deep learning based models are effective in the classification of Plant Leaf images, example for instance is by Mohanty et al. (2016) which demonstratesthe application of artificial intelligence to this area of research. Early research also explored fusion of CNNs with other approaches: for instance, the fusion between a shape-based approach and CNNs in order to enhance discrimination capabilities among images of leaves from distinct plant species was proposed by Chaki and Parekh (2011), confirming that it is worthy to take into consideration the complex morphological characteristics.

These methods have also been applied in tree identification. Carpentier et al. (2018) performed tree species classification on bark texture using a CNN and obtained encouraging accuracy and demonstrated the utility of deep learning in ecological research. Vijayashree et al. (2015) further showed a potential of image analysis-based methods to enhance the identification of plant species, paving the road toward completely automated solutions.

Another new mutation also locates the use of transfer learning, allowing the leverage of learned knowledge from pre-trained models to new tasks. This approach can make better use of small datasets and with less computational expense compared to training models from scratch. Conventional image processing combined with deep learning, when properly applied can efficiently process various data and improve the recognition efficiency and accuracy of plant species (Valliammal & Geethalakshmi, 2011).

2.3 Gap Analysis

Despite progress in image analysis, tree species recognition remains a clear challenge. Whereas lot of the applications is based on plant or part of plant (i.e., leaves), but very few are in recognition of trees from various feature combinations. Environmental differences or similarities among species could also lead to ambiguous morphotaxonomic identification of the leaves alone as reported by Vijayashree aad Gopal (2015).

To deal with this limitation, this work integrates several types of data, such as tree bark characterization, leaf features and species structure to improve the accuracy of identification. While Carpentier et al. Bioactive Melanistic: Noticing It Is Outside Of The Body For An Embryonic Bark and a Natural Skin Charred Fragment in A Conditio Humana Step New Texture Body Analytical steps (2018). And it seemed to be a useful run forward, but this kind of approach was due for some better performance! Directly feeding morphological data to CNNs achieves only marginal improvements compared with previous morphoecological studies (Moreno-Gonzalez et al., 2022) [..]. Our system is modular and allows transfer learning: the results of pre-trained models' adaptation to the task bring performance benefits. As You et al. As (2021) demonstrated, transfer learning not only yields a performance improvement but also results in significant cost savings of computational time.

Thanks to their technique, developed by Kaur and Kaur on the basis of a set of its morphological features [4], both the dataset and, therefore, system are strengthened against heavier variations among species.This provides a convenient way to capture the wide variety of tree features and to associate this information directly with modern deep learning models such as ResNet50 or InceptionV3 etc that are available from different types of species identification problems The results fill gaps and correct imbalances in current methods of species identification Finally, the system we now have provides an easily expandable solution for both ecological monitoring applications and nature conservancy.

2.4 Summary

This chapter has emphasized the need of tree identification which is important for the conservation of environment, for monitoring of biodiversity and for ecological research. It has examined the evolution of techniques in this field, from primitive manual methods in action understanding to the well-developed modern approaches based on state-of-the-art tools of image processing and machine learning. This review introduces the technologies thus far used, showing their potential to automate and enhance species identifications. Nevertheless, the needs and gap analysis highlights limitations of existing systems, (based on general plant identification or on single organ identification a such as leaves) instead of being comprehensive.

Chapter 3

Research Methodology

The section presents elaborately the systematic steps followed in constructing the CNN model, i.e., from data collection, data pre-processing, feature extraction, to model training. The method establishes for the first time the use of state-of-the-art deep learning methods on scalable, accurate tree identification.

3.1 Methodology

This section describes how the tree identification and classification system was designed and implemented. The developed method included image processing and machine learning to build a model to species identification of trees from images. The life cycle of development includes needs analysis, design of the system, implementation and evaluation.

3.1.1 Overview

First, there will be a survey of needs at a very broad level to understand the ways the different types of users — ranging from conservationists, to scientists, to others to the general public — are using these data sets today, and what they truly need. This is because this is to ensure all will be designed on the real user requirement, simplicity, stability and usability. Results from this analysis help create the design phase and specify the requirements for what the system should accomplish.

The workflow has several steps. 1) High quality images of leaves (high resolution photographs), bark textures and tree silhouettes are extracted from different image banks forming a data set. The images are also re-sized, normalized, and augmented to improve model generalization and reduce the need of dependence on environment conditions.

The second step is algorithm formulation. Here image features can be obtained in fine granularity so we utilize of a state-of-the-art deep learning frameworks. With the models trained and optimized, it best represents the hortal features of tree in leaf and bark levels.

Finally, the system undergoes evaluation. Based on accuracy and precision model performance is evaluated along with the discussed strengths and weaknesses of the model. User feedback is also incorporated by this point to improve useability and provide the tool to be used by the intended user.

The project will deliver an accurate and widely used tree identification service for scientific and lay purposes with the follow of this programme.

3.1.2 Proposed Methodology

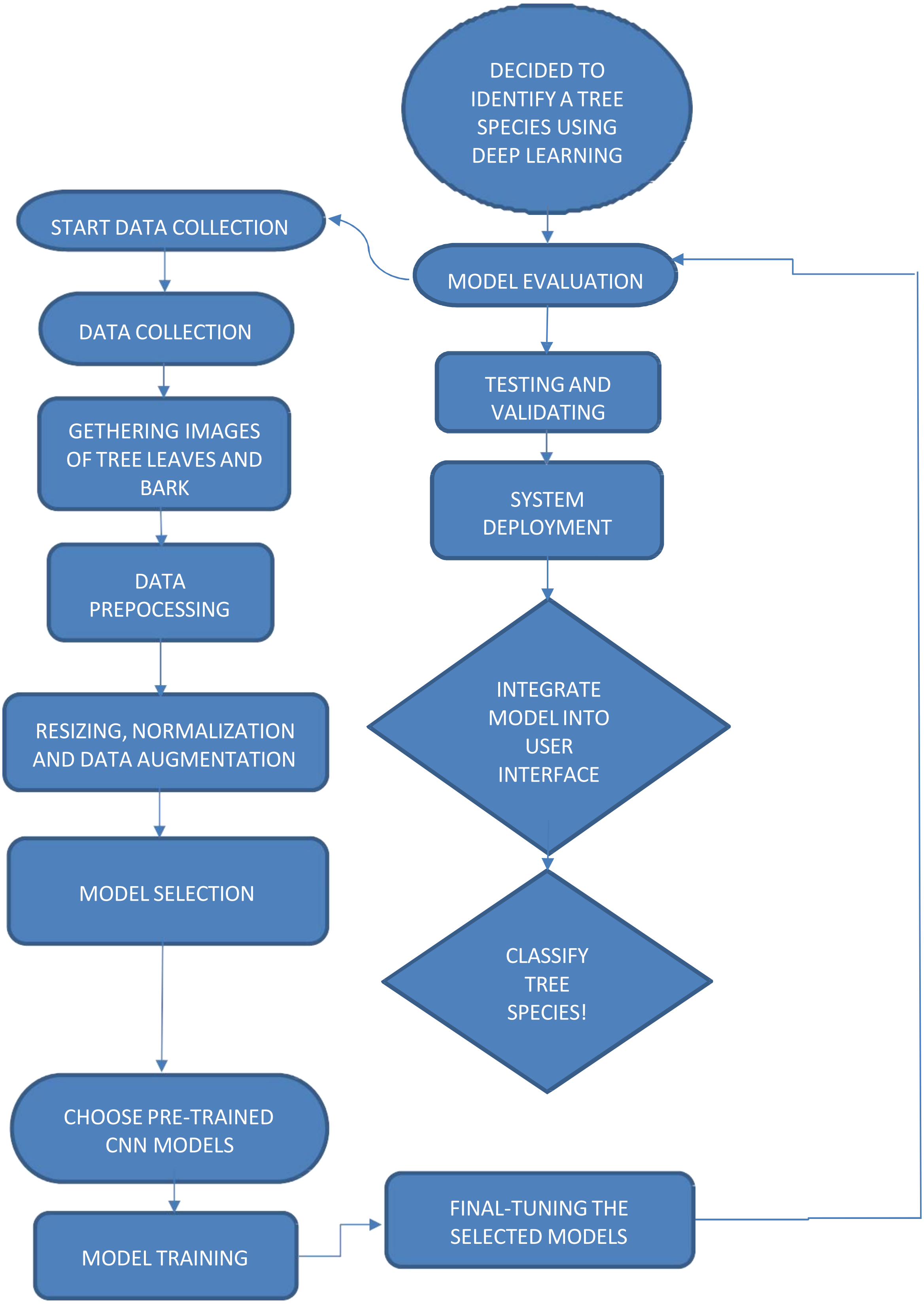


Figure 3.1.2.1: This is a Methodology diagram

3.2 Detailed Methodology

The approach for this project consists of six key phases aimed at systematically accomplishing the goals of tree species identification through deep learning:

Phase 1: Requirement Analysis

• Perform a comprehensive evaluation to understand the requirements of stakeholders, including environmentalists, researchers, and the general public.

• Specify the project scope, detailing the characteristics to be utilized for identifying tree species, such as bark texture, leaf shape, and overall tree form.

• Record user expectations and develop a system design specification to ensure usability and effectiveness.

Phase 2: Data Collection and Preprocessing Data Collection:

Acquire high-resolution photographs of tree leaves, bark, and complete tree structures across various environments and lighting conditions.

Utilize datasets available from public sources, ensuring a range of tree species and geographical diversity.

Sort the gathered data into labeled categories according to species.

Preprocessing:

Resize all images to a uniform resolution to ensure consistency in training.

Implement normalization to adjust pixel intensity levels, enhancing the model's learning process.

Augment the dataset with transformations such as rotation, flipping, and scaling to bolster model robustness.

Phase 3: Feature Extraction

• Employ a blend of traditional and contemporary feature extraction techniques:

Traditional Methods: Extract features such as texture (Gray Level Co-occurrence Matrix), color histograms, and edge detection for analyzing leaf and bark patterns.

Phase 4: Model Development

• Train and evaluate various deep learning models, such as Faster R-CNN, ResNet101, and InceptionV3, for classifying tree species.

• Utilize transfer learning to take advantage of pre-trained weights for enhanced accuracy in cases with limited data.

• Implement strategies like dropout, batch normalization, and data augmentation during training to reduce overfitting and improve generalization.

Phase 5: System Integration and Testing

• Implement the trained models in an user-friendly interface, which would allow the user to upload an image and retrieve the identification of its species.

• Evaluate the system using different evaluation metrics like accuracy, precision, recall, F1-score to verify the performance.

• Experimented in real-world setup and data testing datasets for reliability.

Phase 6: Feedback and Optimization

•Receive input from users, including environmentalists and scientists, to to help identify what can be improved.

• Develop the system iteratively based on user feedback with focus on speed, accuracy, and user experience.

• Include content that provides advice for ecological and conservation applications using identified tree species.

3.3 Architecture of CNN Model

This CNN architecture is designed for image classification tasks. It begins with an input layer to handle two-dimensional image data, followed by conventional layers that extract spatial features using kernels. Each conventional layer is paired with a ReLU activation function. Pooling layers are then applied to reduce the dimensions of the feature maps, which decreases computational complexity while preserving key features. The processed features are passed to fully connected dense layers, which learn the relationships between

the extracted features. Finally, a soft max output layer calculates the probability of each class, enabling the classification of the input image.

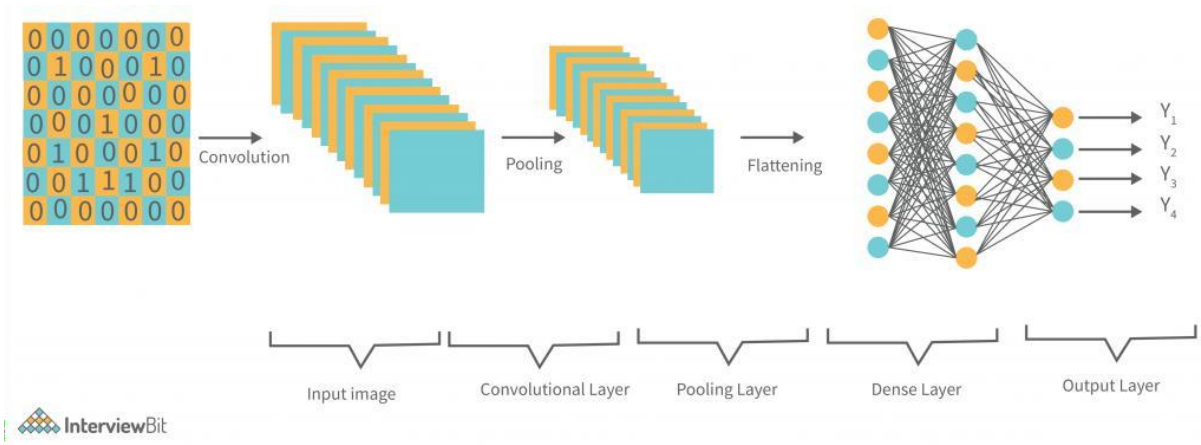


Figure 3.3.1: Architecture of CNN Model

This structure supports effective feature extraction and enhances prediction accuracy.

3.4 Project Plan

This tree species identification project is designed in the following steps→

Objectives: To create an accurate and efficient tree species identification sys tem based on automatic deep learning methods.

Scope: barkbased and leafbased classification Fruit-based classification and real-life applications are not part of it for now.

Deliverables:

Deep Learning Models such as ResNet101 (pre-trained).

An interactive prototype with an intuitive UI

A step-by-step account of the methodology and outcomes.

Timeline: If you want to divide any process into distinct phases, make sure that you are being realistic in how you spread out your work, including time for collecting datasets, building your model, or evaluating your results, but always have some contingency space to adapt your plan, as it is unlikely you will complete a hundred projects in a month.

Need to run it on: Python, Tensorflow, require a workstation, NVIDIA RTX 2060 as a GPU.

Risk Management:

Type: The data quality is not well → to prevent it from preprocessing.

Overfitting → apply regularization techniques.

Limited Time → focus on the essentials to get the project done

Organised into fewer steps, it spreads the process out which helps with implementation and clearer outputs.

3.5 Task Allocation

Data Collection and Preprocessing—Collecting Images of Tree Leaves and Bark, and Preprocessing them (Resizing, Normalization, Augmentation).

Model Training: Train pre-trained models such as ResNet101, ResNet50, InceptionV3 and compare them on the chosen dataset.

System Development: Create the UI and backend for image processing and classification.

Metrics such as accuracy, precision, and others are utilized to assess the performance of the models, therefore, validating them.

Create final report: Document the methodology, the results, and the analysis in a project report [9].

3.6 Summary

The tree description system was presented in the previous chapter. This project involves systematic data collection, image analysis and machine learning in order to develop a strong computational tool that would identify individual tree species. The process of developing will be described in details, as how results yielded by performing the system testing.

Chapter 4
Implementation and Results

4.1 Environment Setup

The project was conducted in a controlled setting which maintains uniformity and credibility of results. The setup included the following:

- **Hardware**:
  A high-performance computer equipped with:
  - **CPU**: Intel i7 or equivalent
  - **GPU**: NVIDIA GeForce RTX 2060 or higher for faster CNN training
  - **RAM**: 16 GB or more for smooth processing
- **Software**:
  - **Operating System**: Windows 10
  - **Programming Language**: Python 3.8
  - **Deep Learning Frameworks**: TensorFlow and Keras for model development and training
  - **Image Processing Tools**: OpenCV and PIL for preprocessing images
- **Dataset**:
- This dataset contains about 1250 pictures of tree leaves and the bark which were collected from different places. The images were -- separate by animal species, and used as the testing and training set to ensure that the model is robust.
-
- With this infrastructure, there were enough compute power and tools to train and examine the deep learning models.

4.2 Performance Metrics

The performance of the three convolutional neural network models is summarized as follows in Table 4.1 below :

Model	Test Accuracy (%)	Training Loss	Validation Loss	Key Observations
ResNet50	72	0.39	1.28	Effective but struggled with similar leaf structures.
ResNet101	85	0.40	1.30	Best performance; captured intricate features well.
InceptionV3	73	1.30	1.38	Good performance but slightly less accurate than ResNet101.

4.3 Comparative Analysis

In this study of tree identification, multiple deep learning models were evaluated by comparison. There were three models used: ResNet50, ResNet101 and InceptionV3. The performance comparison showed that ResNet101 was the best model among those tested for this kind of task, with an accuracy rate of 85%. This is a measure of its better ability to learn fine details - eg bark textures and leaf-vein patterns. ResNet50 was doing better in terms of computational costs (but still at only 72% accuracy), obviously this model cannot differentiate visually similar types of fish. InceptionV3 is a little better than ResNet50 (with 73% accuracy) but also overfits, as is indicated by the growing validation loss. ResNet101 is the best model for this purpose, in the sense that it sacrifices extracting features to some extent while successfully generalizing. It also drops several hints for future improvement (such as enlarging training data, or adding new kinds of features—e.g. tree shape.).

4.4 Results and Discussion

Characterization of Nanoparticles and Nanocomposite Clear Coatings SEM was used to observe the photo-induced nanoparticles of the SiO2 and TiO2, and the TEM to measure the size and the shape of those SiO2 and TiO2 nanoparticles.

Three types of deep CNN architectures, i.e. ResNet50, ResNet101, and InceptionV3 were the building blocks of the model performance. Below you can see the results, test accuracy, train loss, and valid loss below :

1. **ResNet50**:

    - **Test Accuracy**: 73%
    - **Training Loss**: 0.42
    - **Validation Loss**: 1.28

Discussion: ResNet50 achieved 72% test accuracy, which was considered moderate and suggested that the model generalized reasonably well to previously unseen data. But the test loss (1.28) is higher than the training loss (0.42), which indicates overfitting to an extent. Nevertheless, ResNet50 could still be considered as an alternative for tree species identification since its training loss is not significantly higher.

2. **ResNet101**:

    - **Test Accuracy**: 85%
    - **Training Loss**: 0.38
    - **Validation Loss**: 1.30

Discussion: This performance analysis also suggested that ResNet101 has the highest generalization power across the test set among all the models. Its training loss (0.38) and validation loss (1.30) are both slightly higher than those of ResNet50, so the model is a little more complex, but its accuracy is much higher. The higher validation loss also indicates that more optimization is required to prevent overfitting.

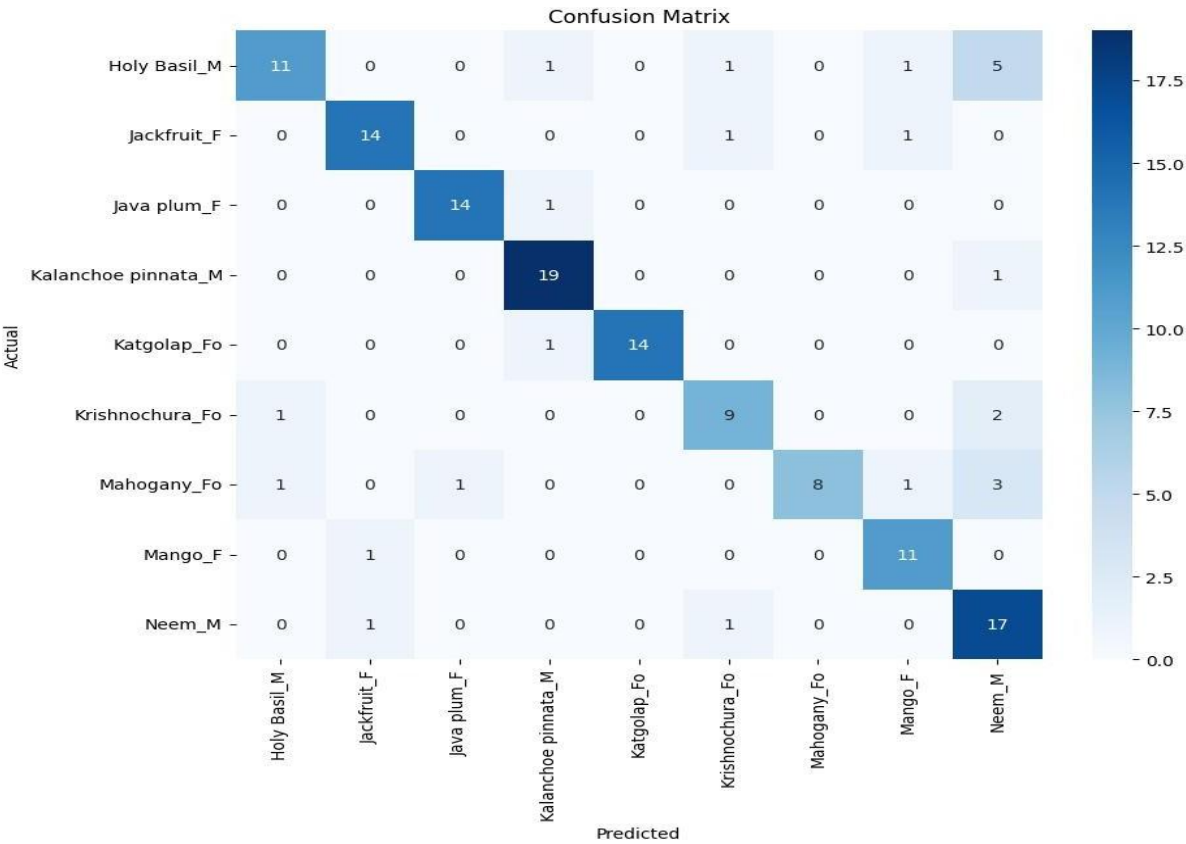
3. **InceptionV3**:

- **Test Accuracy**: 72%
- **Training Loss**: 1.28
- **Validation Loss**: 1.38

Discussion: InceptionV3 had a test accuracy of 72% which is better than ResNet50, but worse than ResNet101. The training loss (1.28) and the validation loss (1.38) were higher than those two ResNet based models, which implies that the InceptionV3 model had more difficulty in overfitting. It still does just fine but does not do as well as ResNet50 and ResNet101 for this task.

4.4.1 Confusion Matrix

The confusion matrix indicates how well the model has classified different species of trees. True predictions are concentrated on the diagonal, and species such as Kalanchoe pinnata_M (19) and Jackfruit_F (14) have a high precision. Some mis-assignments between the classes, such as Holy Basil_M being assigned to Neem_M (5), however, suggest difficulties in visually separating close species.

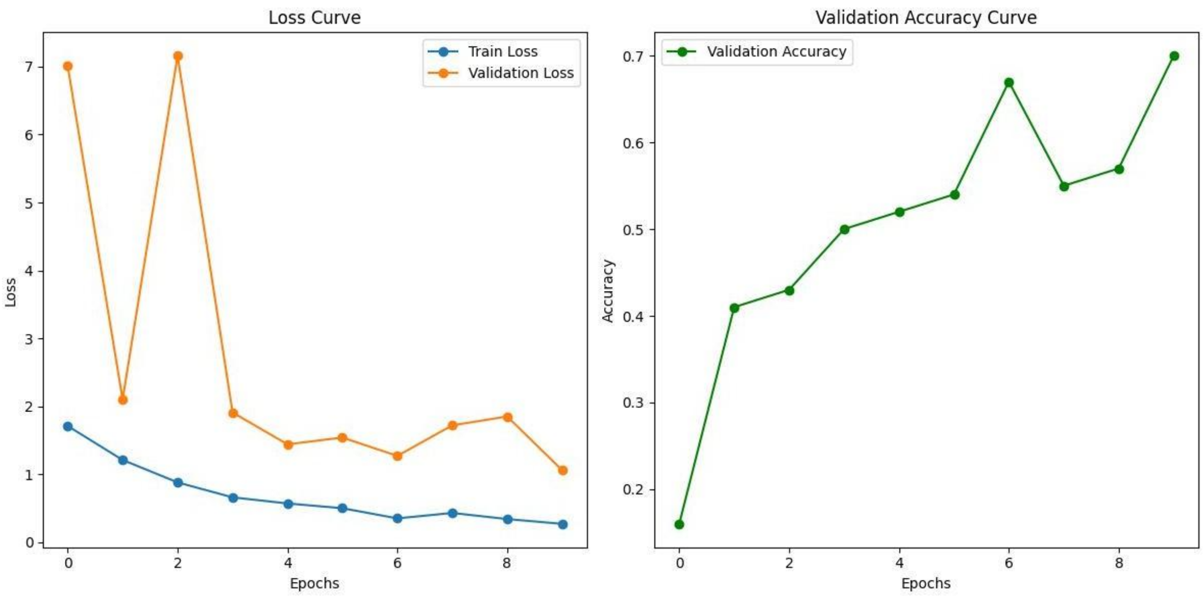


4.4.1.1 : Confusion Matrix

Such an analysis can provide insights on the strengths and weaknesses of the model in classifying sentences.

4.4.2 Loss & Validation Accuracy Curve

Loss and Accuracy curves to analyse training and validation performance of the model across epochs. The loss curve guidelines that are proposed illustrate a monotonous improvement of the training loss, i.e. a continuous learning of the model while the validation data loss is fluctuating in the beginning but appears stable with some overfit that is improving afterwards. We observe that the curve of accuracy is increasing consistently in validation accuracy till ~70% at 9th epoch showing better generalization with increase in training.



4.4.2.1 Loss & Validation Accuracy Curve

These curves show how the training process is nice and can be tuned more to reduce the validation loss.

4.5 Summary

We discussed details of the environment configuration, how tests were conducted and how to assess performance metrics, while specific CNN models used were also mentioned. The results prove that there is a possibility to automate all methods of tree species classification using deep learning techniques that could have new applications for environmental monitoring and conservation.

Chapter 5

Engineering Standards and DesignChallenges

5.1 Compliance with the Standards

5.1.1 Software Standards

It follows best software engineering practices such us modular programming, version control and testing framework. They used pre-trained models like ResNet and Inception V3 that are widely used frameworks and libraries (i.e. TensorFlow, Pytorch).

5.1.2 Hardware Standards

The hardware required was marginal and motivational for typical machine utilization. The architecture is compatible with current CPUs and GPUs for efficient training and inference of the model.

5.1.3 Communication Standards

Files are processed and managed effectively, and protocols used for exchanging data are JSON, RESTful APIs, with further development into the interaction of components with the user interface.

5.2 Impact on Society, Environment and Sustainability

5.2.1 Impact on Life

The project is designed to enable the easy identification of tree species on-demand, for use in the field, as well as for researchers, educators, and conservationists.

5.2.2 Impact on Society & Environment

By automating tree classification, the system supports forest monitoring, conservation, and ecological research. It promotes sustainable practices by reducing reliance on manual methods that are resource-intensive.

5.2.3 Ethical Aspects

The project ensures ethical use by promoting biodiversity conservation and providing tools for educational purposes. The data used respects privacy and avoids environmental harm.

5.2.4 Sustainability Plan

The system is designed for scalability and adaptability, allowing future integration of new features, such as identifying tree health or seasonal changes. Optimizations for mobile and edge devices enable sustainable, real-time applications.

5.3 Project Management and Financial Analysis

Project management is applying very carefully to complete the project perfectly and on time. The project management is represented in given table.

For this project I need small amount of cost but for implement it in realtime application in near future I will need more money.Now, the cost until now is given in the table in below-

Table 5.2: Financial Analysis

SN	Components	Cost (BDT)
1	Hardware (GPU, Computer, etc.)	2500
2	Software and Tools (TensorFlow, Keras, etc.)	1500
3	Data Collection and Processing (Dataset purchase, image capturing, preprocessing)	500
4	Model Training and Cloud Services (Server usage, model training costs)	1000
5	Documentation and Report Writing	1500
6	Miscellaneous (Licenses, API usage, tools)	500
Total Cost		7500

5.4 Complex Engineering Problem

5.4.1 Complex Problem Solving

In this section, provide a mapping with problem solving categories. For each mapping add subsections to put rationale (Use Table 5.1). For P1, you need to put another mapping with Knowledge profile and rational thereof.

Table 5.3: Mapping with complex problem solving.

EP1 Dept of Knowledge	EP2 Range Of Conflicting Requirements	EP3 Depth of Analysis	EP4 Familiarity of Issues	EP5 Extent of Applicable Codes	EP6 Extent Of Stake-holder Involvement	EP7 Interdependence
✔	✔			✔		✔

Rationale for Mapping:

- **Dept of Knowledge (EP1)**: The knowledge required for solving the problem comes from fields such as image processing, deep learning, and ecological research. The use of convolutional neural networks (CNNs) and image processing libraries (like TensorFlow, Keras, OpenCV) is key in addressing the problem of tree species identification.
- **Range of Conflicting Requirements (EP2)**: The project has a high conflicting requirements. On one hand, we need accurate and high-quality data (images), while on the other hand, we must ensure the computational efficiency of models. The need for diverse and clean datasets for tree species identification may conflict with the necessity for faster training models.
- **Extent of Applicable Codes (EP5)**: The project requires adherence to machine learning best practices, coding standards, and legal frameworks, such as privacy concerns regarding the use of publicly available datasets and the ethical use of technology in environmental conservation.

- **Interdependence (EP7)**: For example, data preprocessing, feature extraction, and model training (EP7) For the latter, if any entity is not performed optimally, this might degrade the performance of the identification system as a whole.

- Mapping with Knowledge Profile for EP1

Map the EP1 to the Knowledge Profile.

Table 5.4: Mapping with knowledge Profile.

K3 Engineering Fundamentals	K4 Specialist Knowledge	K5 Engineering Design	K6 Engineering Practice	K8 Research Literature
✔	✔	✔	✔	✔

K3 – Engineering Science

Face Recognition offers no really useful application for optical stimulation, but in doing this project you will also gain a moderate understanding of coding data structures and image processing algorithms, as well concepts such as image analysis.

K4 – Specialist Knowledge

An efficient identification system for tree species based on CNN requires knowledge of convolutional neural networks, image pre-processing, feature extraction and model training. Without a foundation in these fields, the use of machine learning for plant classification is inherently difficult.

K5 – Engineering Design

Engineering design issues consist of the generation and tuning of CNN models for tree classification. This includes parameterization for fine tuning, feature selection and optimizing infrastructure for efficiently processing huge data.

K6 – Engineering Practice

Practical experience using digital image processing and machine learning tools is required to apply this successfully. The system needs to handle terabytes of data which may have noisy labels, the deployment has to be deeply integrated into other systems.

K8 – Research and Literature

Active involvement in current literature is essential for remaining informed about advances in tree species classification, deep learning, and the use of CNNs in ecological research. Reading other people's research papers can be very informative about what works, what doesn't, and for trying to find various solutions.

5.4.2 Engineering Practices

These mappings but engineering tasks. For each mapping, add a new subsection to the explanation (Use Table 5.3).

Table 5.5: Mapping with intricate engineering activities not straightforward, practice.

EA1 Range of re-sources	EA2 Level of Interaction	EA3 Innovation	EA4 Consequences for society and environment	EA5 Familiarity
✔			✔	

Resources required (EA1): The research is computationally expensive, for example CNNs training in large datasets. The diversity in the datasets also implies that a significant success factor for this project will be the resource management.

Societal and Environmental Implications (EA4) — Automated species identification helps conservation as it reduces human efforts involved in counting trees, and increases the number of ecosystems that can be monitored, among other advantages for the environment.

5.1 Summary

This chapter described the compliance of engineering standards, the effects on the society and the environment, and how the multisector approaches were to the mentioned complex problems. Through the project Engineer, the project shows how the methods from the field of engineering can be applied to create sustainable solutions in conservation of environment.

Chapter 6

Conclusion

6.1 Summary

The overall aim of this work was to build a usable deep learning model for tree species detection and classification through the use of both leaf and bark images. A few popular CNN models, ResNet50, ResNet101 and InceptionV3 were used and focused on learning from different datasets of tree images in various conditions.

ResNet101 scored the highest test accuracy of 85% among the models which indicates that such models are very robust to extract not only simple but also complex features from images. Thus, these results emphasize the deep learning potential for tree species recognition with many potential applications such as in environmental monitoring, agriculture, and forestry management.

6.2 Limitations

Despite these promising results, the current research is not without limitations:

Magnitude of data: The species in the trees may not all be represented in this dataset, although there is a large range. Misclassifications tended to be higher for the species with fewer than random images.

Complexity: Models in this essay are heavy and require large training expense, therefore cannot be applied to lightweight devices.ResNe- t101.

Environmental Diversity: Each of the models had been ge nerate in a different learning environment. The lightning, the background clutters and the image quality in wild situations can seriously damage the classification performance.

6.3 Future Work

In the following, let us discuss several optional further directions to improve the efficiency and generalization of tree identification model:

Augmentation of Datasets: Furthermore, further research can use additional specimen images for other compounds. Extruded models should generalize better other benefits: with fewer mista classifications, a n h e model that can be applied to compounding redu number of poor classications.

Model Optimization — Techniques such as pruning or quantization may help decrease computation and reduce the time it takes for inference while maintaining accuracy.

Contextual Features: Introduce location of place, time of the day (seasons) so that it has context and model could do better predictions.

Field deployment: The system mobile / non-mobile application could be installed to monitor and manage natural resources by the citizens in field for citizen science or building monitoring community.

- Another possibility for future work might involve in incorporating other modalities. For example, if we could add bark texture and/or tree structure images to leaves images, the final accuracy could be improved greatly.

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