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A Few-Shot Learning Framework for Real-World Bark Texture Classification in Indian Tree Species

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ABSTRACT

In this study, address the research gap in Indian tree species classification by constructing a novel dataset comprising real-world tree bark images of species aged 25 years and above. The dataset was collected in diverse natural settings to ensure variability in lighting, background, and tree maturity. To enhance classification performance, employ a Few-Shot Learning (FSL) approach using a Prototypical Network. Experiment includes image preprocessing, feature extraction, and metric-based classification. Utilize ResNet18 as a feature extractor, replacing its fully connected layer with an identity mapping to obtain meaningful feature embedding's. The training process follows an episodic learning paradigm, where each task consists of a support set and a query set to simulate real-world classification scenarios with limited labeled data. Our results highlight the feasibility of Few-Shot Learning for tree species classification, providing a scalable solution for biodiversity monitoring and timber industry applications.

1. INTRODUCTION

Tree species classification is essential for forestry management, biodiversity conservation, and the timber industry. Traditional classification methods often depend on large labeled datasets and handcrafted features, which pose challenges in real-world applications due to the limited availability of annotated data. While existing datasets cover various tree species, they predominantly focus on non-Indian species, highlighting a significant research gap in the classification of Indian tree species, especially using bark texture. To bridge this gap, we have developed a novel real-world dataset comprising tree bark images from Indian species aged 25 years and older, as trees in this age range are well-suited for timber applications [3].The dataset is collected in diverse environmental conditions to incorporate variations in lighting, background, and bark maturity, making it a valuable resource for deep learning-based classification models.

Deep learning models such as Convolutional Neural

Networks (CNNs) have shown remarkable success in image classification tasks [4], but their performance is highly dependent on large-scale annotated datasets. In scenarios where labeled data is scarce, Few-Shot Learning (FSL) techniques have emerged as a promising solution. FSL enables models to generalize from a small number of training examples by leveraging metric-based learning, meta-learning, or transfer learning techniques [1]. Prototypical Networks, a widely used metric-based FSL approach, classify unseen samples by computing distances between query image embeddings and class prototypes derived from a small support set [2]. This technique is particularly useful for tree species classification, where acquiring extensive labeled datasets is both time-consuming and resource-intensive.

In this study, implement an FSL-based classification framework using Prototypical Networks, with ResNet18 serving as the feature extractor. The fully connected layer of ResNet18 is replaced with an identity mapping to extract high-dimensional feature embedding's. The model is trained in an episodic fashion, where each task consists of a few support and query samples to mimic real-world classification challenges. Additionally, data augmentation techniques, including resizing, normalization, and color transformations, are applied to enhance model generalization. The proposed approach is evaluated using accuracy metrics, confusion matrices, and classification reports, demonstrating its effectiveness in Indian tree species classification. The results validate the feasibility of FSL in real-world applications, offering a scalable solution for tree identification and ecological studies.

II. RELATED WORK

Sen et al [6]. Have made significant contributions to hyper spectral image (HSI) classification, particularly focusing on addressing the challenges posed by limited labeled samples. Their work often explores advanced deep learning techniques, including transfer learning, few-shot learning, and the development of lightweight models, to enhance the performance of HSI classification. They emphasize bridging the gap between the data-intensive nature of deep learning models and the scarcity of labeled HSI samples by leveraging innovative model architectures and optimization strategies.

Monika et al [7]. have focused on improving image classification performance by integrating deep learning features with traditional handcrafted feature extraction methods. While deep learning models like VGG19 have shown remarkable results, they still face challenges in capturing all critical image information, which can reduce classification accuracy. To address this, the study combines deep features from VGG19 with features extracted using methods like SIFT, SURF, ORB, and Shi-Tomasi corner detection. These combined features are classified using machine learning algorithms, including Gaussian Naïve Bayes, Decision Tree, Random Forest, and XGBoost. Experiments on the Caltech-101 dataset show that the Random Forest classifier with combined features achieves 93.73% accuracy, outperforming other methods. The research highlights that a hybrid approach—leveraging both deep learning and handcrafted features—provides superior results compared to relying on a single feature extraction method.

Lin et al [8]. Proposed a contrastive self-supervised learning (SSL) algorithm for hyperspectral image (HSI) classification, addressing the challenge of limited labeled samples. Their method uses an HSI-specific augmentation module to generate sample pairs and a Siamese network-based SSL model to extract features. The model is then fine-tuned with few labeled samples to improve classification performance. Tests on two HSI datasets showed the algorithm's effectiveness in achieving superior results with minimal labeled data.

Sparsh et al [9]. Conducted a comprehensive survey on using deep learning for underwater image classification, targeting objects like fish, plankton, coral reefs, and submarines. This classification is critical for assessing water quality, protecting marine life, and applications in oceanography, defense, and underwater exploration. The study highlights the similarities and differences among various methods, positioning underwater image classification as a pivotal application to evaluate the potential of deep learning. The survey aims to inform researchers about the state-of-the-art techniques and inspire advancements in this field.

Yongke et al [10]. Proposed a deep-learning-based method for wood species recognition to address the limitations of traditional shallow models with low accuracy and poor generalization. Their approach uses a 20X amplifying glass to capture wood images, extracts features with a ResNet50 neural network, refines these features using linear discriminant analysis (LDA), and classifies species with a KNN classifier. Transfer learning was employed to enhance performance on their small dataset of about 3,000 images across 25 rare wood species. Experiments demonstrated superior accuracy and generalization compared to traditional methods, validating the method's effectiveness even with limited data.

Yong et al [11]. Reviewed the applications of deep learning (DL) in forestry, highlighting its use in areas like sawn timber quality evaluation, forest resource surveys, tree species identification, wood moisture prediction, and forestry text classification. They found that DL, particularly CNNs and YOLO algorithms, improves efficiency in tasks like surface evaluation and species recognition. DL also offers valuable methods for remote sensing image recognition and wood moisture prediction. The paper concludes by predicting future trends in DL applications for high-end forestry equipment, microscopic research, and smart forestry.

İsmail et al [12]. Explored the use of deep learning, particularly convolutional neural networks (CNNs), for wood species classification, replacing traditional methods that require extensive knowledge of wood anatomy and are often time-consuming and costly. Their study focused on the WOOD-AUTH dataset, which includes macroscopic images of 12 wood species from three different wood sections: cross, radial, and tangential. They evaluated various deep learning architectures, including ResNet-50, Inception V3, Xception, and VGG19, using transfer learning. The results showed that Xception outperformed the other models, achieving a classification accuracy of 95.88%.

Peyman et al [13]. Developed a transductive meta-learning method to enhance few-shot image classification by leveraging unlabeled instances. Their approach combines a regularized Mahalanobis-distance-based soft k-means clustering procedure with a modified neural adaptive feature extractor to improve test-time classification accuracy. The method was evaluated on transductive few-shot learning tasks, where the goal is to predict labels for query examples using support examples. The results showed state-of-the-art performance on the Meta-Dataset, mini-ImageNet, and tiered-ImageNet benchmarks.

III. Overview of Dataset

To support research in tree species classification, authors developed and published a dataset focusing on tree species from the southwestern region of Karnataka, with a special emphasis on Bangalore-centric species. The dataset consists of 558 high-resolution images covering 22 distinct tree species, curated for applications in forestry, timber classification, and ecological studies.

This dataset has been made publicly available at https://data.mendeley.com/datasets/v8xyr7tnbx/1[23].

A comprehensive description of the dataset creation process, including data collection methods, preprocessing, and annotation details, is provided in a separate study, which is currently under review.

The Table 1 and Table 2 below provides detailed information about the created dataset, including species names, the number of images, image formats, sizes & Format.

Table 1 Summary of the Bark Texture Recognition of Indian Trees: A Bangalore-Centric Dataset [23]

Parameters	*Values*
Total number of images	558
Original image size	Variable in size
Number of classes	22
Resized Image	224 X 224
Converted Image format	RGB JPEG images
Total size of dataset	133 MB

2. Detailed overview of the dataset [23]

SL No.	Species Name	Scientific names	No. of Images
01	Arali Tree	Ficus benghalensis	14
02	Atti Tree	Ficus racemosa	14
03	Bagan Tree	Ficus benghalensis	24
04	Bombax Ceiba	Silk Cotton Tree	23
05	Coconut Tree	Cocos nucifera	21
06	Gooje Tree	Terminalia arjuna	19
07	Honge Tree	Pongamia pinnata	19
08	Jackfruit Tree	Artocarpus heterophyllus	43
09	Jamoon Tree	Syzygium cumini	47
10	Java Fig	Ficus microcarpa	27
11	Java Plum	Syzygium jambos	23
12	Lemon Scented Gum Tree	Eucalyptus citriodora	27
13	Mango Tree	Mangifera indica	32

14	Pink Trumpet Tree	Tabebuia impetiginosa	24
15	Rain Tree	Samanea saman	22
16	Red Silk Cotton	Bombax ceiba	22
17	Sampige Tree	Michelia champaca	24
18	Silver Tree	Grevillea robusta	49
19	Thega Tree	Tectona grandis	20
20	Tunga Oil Tree	Vateria indica	19
21	White Fig	Ficus virens	21
22	White Silk Cotton	Bombax ceiba	25

Figure 1 showcase sample images from each class of the dataset, representing the distinct bark textures of 22 Indian tree species. These examples illustrate the diversity and unique patterns captured to support robust classification models.

Figure 1. Sample images of each class from the A Bangalore-Centric Dataset

IV. METHODOLOGY

Given the limited number of collected images, traditional deep learning models may struggle to generalize effectively. To address this challenge, Implemented few-shot learning (FSL) techniques, which are well-suited for scenarios with scarce labeled data. FSL enables models to learn from a small number of examples by leveraging prior knowledge and extracting meaningful representations with minimal supervision.

In this study, implement Prototypical Networks for tree species classification. This approach learns a metric space in which classification is performed by measuring distances to prototype representations of each species. Additionally, pre-trained model ResNet18 is explored in combination with FSL to enhance feature extraction.

The overall workflow of the proposed method is illustrated in Figure 2. The block diagram outlines the process of dataset preprocessing, feature extraction using ResNet18, and classification using Prototypical Networks. It represents how few-shot learning is leveraged for tree species classification, addressing the challenge of limited training data.

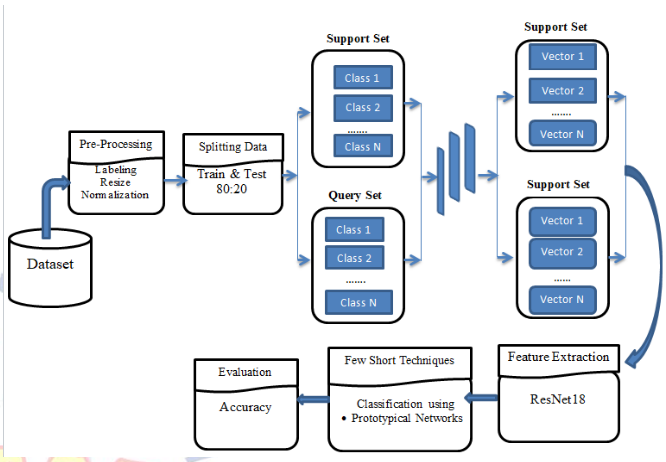

Figure 2: Block diagram of proposed experiment

A. Data pre-processing

The images were resized, normalized, and converted to JPEG for consistency. Each was manually labeled based on expert verification and structured for seamless model training.

B. Data Splitting

The dataset was splited into 80% for training and 20% for testing, ensuring a balanced distribution for effective model evaluation.

C. Support and Query Set Formation

To implement Few-Shot Learning (FSL), the dataset was divided into two key sets:

• Support Set: A small number of labeled examples per class (K-shot). Each class in the support set contained K samples that served as references for classification.

• Query Set: Unlabeled samples that the model needed to classify based on the learned support set prototypes.

D. Feature Extraction Using ResNet18

Residual Blocks

The fundamental innovation in ResNet is the introduction of residual blocks, which utilize skip connections to bypass one or more layers. This design mitigates the vanishing gradient problem by allowing gradients to flow more efficiently through the network. A residual block is mathematically represented as in Equation 1:

$$y=F(x, \{Wi\}) +x \longrightarrow (1)$$

Where:

- y is the output,
- x is the input, and
- F(x, {Wi}) represents the residual mapping that the network learns.

By preserving key information across layers, residual blocks improve convergence and enhance training stability in deep networks.

Skip Connections

Skip connections facilitate direct pathways for information flow by allowing the input to bypass intermediate layers and be added directly to the output. This mechanism preserves crucial features and gradients, making it easier to train very deep networks. The skip connection follows the same mathematical formulation as the residual block shown in Equation 2:

$$y=F(x, \{Wi\}) +x \longrightarrow (2)$$

While both concepts share the same formula, the residual block refers to the architectural unit incorporating the skip connection, while skip connections describe the underlying mechanism enabling effective deep learning.

Network Depth

ResNet-18 consists of 18 layers, including:

- Convolutional layers for feature extraction,
- Batch normalization layers to stabilize training,
- ReLU activation functions for non-linearity,
- Pooling layers for down sampling, and
- Fully connected layers for final classification.

E. Prototype Computation and Classification Using Prototypical Networks

After extracting feature representations using ResNet-18, the classification process was carried out using a Prototypical Network, which operates based on class prototypes.

Prototype Computation

For each class in the support set, a prototype vector was computed as the mean of the feature embeddings of all support samples in that class. This is shown in the equation 3.

$$C_k = \frac{1}{|S_k|}\sum_{x_i \in S_k} f_0(x_i) \longrightarrow (3)$$

Where:

- C_k is the prototype of class k,
- S_k represents the set of support examples for class k, and
- $f_0(x_i)$ is the feature embedding extracted from ResNet-18.

These prototypes serve as the class representatives for classification.

Query Classification

Each query sample was classified by measuring the Euclidean distance between its feature representation and the class prototypes:

$$d(f_0(x), C_k = \|f_0(x) - C_k\| \longrightarrow \quad (4)$$

Where:

- $d(f_0(x), C_k$ Represents the squared Euclidean distance between the query sample's feature representation and the class prototype.
- $f_0(x)$ Is the feature embedding of the query sample xxx, extracted using ResNet-18.
- C_k Is the prototype (centroid) of class k, computed as the mean of the support set embeddings
- ||·||2 denotes the squared L2 norm (Euclidean distance).

The query image was assigned to the class with the closest prototype, effectively grouping it with the most similar support class.

V. Experimental Setup

A. Hardware & Software Used

The experiments were conducted on a system with the following specifications:
Hardware:

- CPU: Intel Core i7/i9
- RAM: 4 GB
- Storage: SSD 4 GB

Software & Frameworks:

- OS: Windows 10
- Programming Language: Python 3.9
- Deep Learning Framework: PyTorch
- Image Processing: OpenCV, Pillow
- Visualization: Matplotlib, Seaborn

B. Hyperparameters

The following hyperparameters were set for model training:

Table 3: Few-Shot Learning and Training Parameters

Parameter Type	Parameter	Value
Few-Shot Learning Parameters	n-way	5 (number of classes per episode)
	k-shot	5 (support samples per class)
	Query samples per class	15
Training Parameters	Batch Size	1 (for episodic training)
	Learning Rate	0.01
	Optimizer	Adam
	Number of Epochs	10
Data Processing Parameters	Image Size	224 × 224 pixels
	Normalization (Mean)	[0.485, 0.456, 0.406]
	Normalization (Std Dev)	[0.229, 0.224, 0.225]

The Table 3 shows the hyperparameter configuration used for few-Shot Learning and training. It includes key parameters for episodic learning, training strategy, and data preprocessing.

C. Training Strategy

The training procedure involved episodic learning, where each episode consisted of a randomly sampled n-way k-shot task.

- **Step 1:** The support and query sets were selected for each episode.
- **Step 2:** Feature embeddings were extracted using a pre-trained ResNet-18 model.
- **Step 3:** Class prototypes are computed as the mean of support set embeddings.
- **Step 4:** Query embeddings were classified based on their proximity to the prototypes using Euclidean distance.
- **Step 5:** The model is optimized using the negative Euclidean distance + Cross-Entropy loss.
- **Step 6:** The model is evaluated on a test set after each epoch to monitor accuracy and loss trends.

D. Evaluation Metrics

The model's effectiveness was assessed using standard classification metrics:

- **Accuracy:** The ratio of correctly classified query samples to the total number of queries:

$$Accuracy = \frac{Correct\ Prediction}{Total\ Queries} X100$$

- **Precision & Recall:** Evaluating the model's ability to correctly classify each species while minimizing false positives and false negatives.
- **F1-Score:** A balance between precision and recall to measure overall classification effectiveness.

VI. Experimental Results

A. Model Performance Metrics

The proposed model was evaluated using accuracy, precision, recall, and F1-score. The classification performance for each species was analyzed, and the overall accuracy of the model was computed.

B. Training and Validation Performance

The training process was conducted over 10 epochs, and the model's accuracy and loss trends were recorded. The training and validation accuracy steadily improved, reaching a peak accuracy of 99.7% for certain tree species.

The Figure 3 & Figure 4 below shows the accuracy and loss curves for training and test sets.

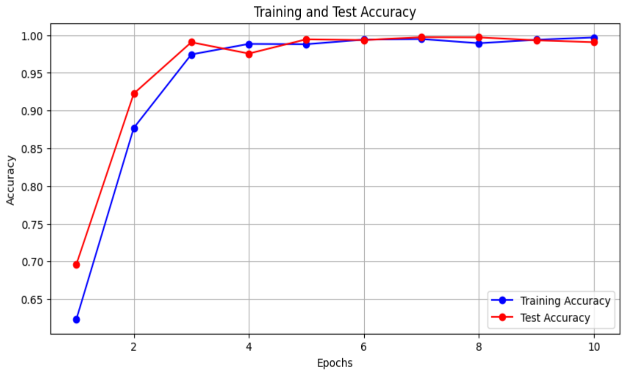

Figure 3. Training and Test accuracy curve graph

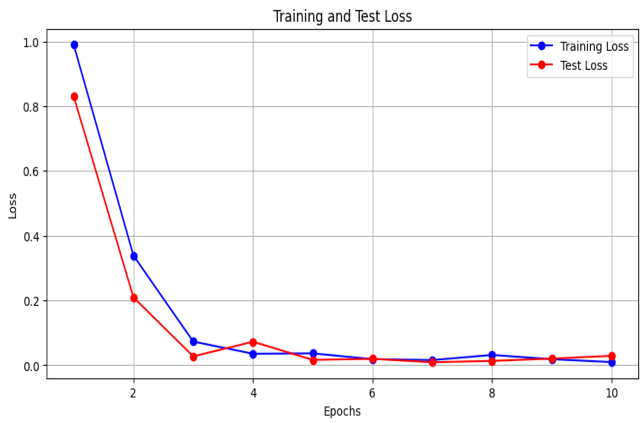

Figure 4. Training and Test accuracy curve graph

From The Figure 3 (Training and Test Accuracy), it is observed that both training and test accuracy increase rapidly within the first 3 epochs and stabilize close to 99-100%, indicating efficient learning with no significant over fitting.

From The Figure 4 (Training and Test Loss), the loss decreases sharply within the first few epochs and stabilizes near zero, confirming that the model has learned the dataset well with minimal classification errors.

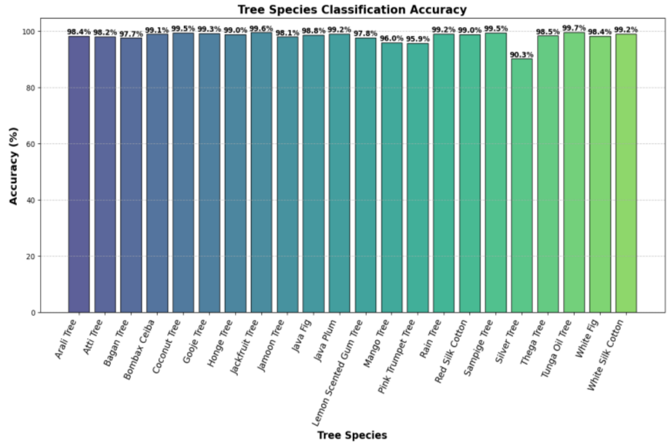

Figure 5. Classification accuracy of each class

The Figure 5 shows the class-wise classification accuracy, illustrating how well the model performs for each individual class.

Table 4: Overall Classification Performance Metrics

Metric	Value (%)
Accuracy	99.05
Precision	99.05
Recall	98.99
F1-score	98.99

From Table 4: Overall Classification Performance Metrics, it is observed that the model achieves high accuracy of 00.05, precision as 99.05, recall as 98.99, and F1-score as 98.99, indicating robust classification performance.

C. Comparison with Existing Models

To validate the effectiveness of the proposed model, its performance was compared with authors previous work [18] deep learning models commonly used for texture classification. The comparison includes models such as VGG16, ResNet50, and MobileNet etc.

Table 5 presents the accuracy of various models on the same dataset. The proposed model outperforms these models, demonstrating superior classification accuracy and robustness.

Table 5: Performance Comparison of Different Models

Sl No	Model	Accuracy (%)	Precision (%)	Recall (%)
01	Basic CNN	30.00	44.45	20.10
02	ResNet-50	83.33	84.53	84.53
03	MobileNet	80.83	87.62	87.82
04	Inception V3	90.50	94.76	94.82

05	VGG16	85.83	89.90	76.78
06	ResNet-101	40.83	42.88	44.08
07	ResNet-152	39.17	43.02	39.62
08	DenseNet-121	92.50	93.52	93.88
09	VGG19	85.00	88.63	85.00
10	MobileNet V2	87.50	90.23	88.53
11	Xception	87.50	87.54	83.67
12	EfficientNet	10.00	00.00	00.00
13	**Proposed Model**	**99.05**	**99.05**	**98.99**

As observed in Table 5, the comparative analysis of various models indicates that the proposed method outperformed the others by achieving the highest accuracy

VII. Conclusion

This research effectively fills the gap in Indian tree species classification research by creating a new bark image dataset of mature trees 25 years and older, photographed in various natural environments. A Few-Shot Learning (FSL) framework based on a Prototypical Network with ResNet18 as the feature extractor was utilized to address the problem of few labeled data. By substituting the fully connected layer with an identity mapping, semantically meaningful feature embedding's were generated, and the episodic learning setting mimicked actual application scenarios in real-world classification. The suggested approach attained a remarkably high accuracy of 99.05%, which reflects its ability and reliability. This outcome showcases the promise of FSL-based models for real-time, scalable applications in biodiversity tracking and the wood industry.

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Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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