Deep Learning (ResNet50) – Based Paddy Disease Classification Using MPI Parallelism

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***Abstract*— In this particular field of agriculture, the identification and classification of crop disease play a vital role in optimizing the yields and minimizing the loses of the crops. In our project, we propose a new approach for paddy disease classification using well known deep learning architecture ResNet-50(Residual Neural Networks) and combing it with message passing interface (MPI) for the parallelism. The use of ResNet-50 allows for the extraction of features from paddy disease images and enables for precise classification. Furthermore, the inclusion of MPI facilitates efficient parallel processing, enabling the rapid analysis of large datasets. Through extensive experimentation and validation, our proposed methodology achieved a best classification accuracy of 95%, underscoring it efficiency and had potential for real world deployment in agriculture fields. This project signifies a significant advancement towards accurate paddy disease identification. Keywords—ResNet50, Extreme Gradient Boost, Random Forest, Decision Trees, Ensemble methods. Our approach not only demonstrates remarkable accuracy in paddy disease classification but also showcases the scalability and computational efficiency afforded by MPI parallelism. By integrating cutting-edge deep learning techniques with parallel processing capabilities, our methodology paves the way for scalable and timely disease diagnosis in agricultural field.**

I. INTRODUCTION

Identifying and classifying crop diseases in agriculture remains key to improving yields and preventing losses of paddy, one of the world's major crops, is particularly susceptible to various diseases, and could severely affect its yield. Traditional methods of disease detection and classification often rely on manual inspection, which can be time consuming, labor intensive and error prone Consequently automated systems that can accurately detect and classify paddy diseases of the plant. In recent years, deep learning techniques have emerged as powerful tools for image classification tasks, showing remarkable success in various fields. These techniques residual neural networks (ResNets) have received a great deal of attention for their ability to efficiently capture complex features from images Advents, such as the Message Passing Interface (MPI) have opened up ways to speed up computation and process large amounts of data successful.

Due to the importance of automatically and accurately classifying the paddy diseases, this work proposes a new method that exploits the capabilities of ResNet-50 a Residual Neural Networks, and combines it with MPI suggest a parallel project. Taking advantage of the feature extraction of ResNet-50 and the parallel computing capabilities of MPI, our approach aims to provide a robust and scalable solution for paddy disease classification.

Through this project, we seek to address the following objectives:

- Develop a deep learning-based framework using ResNet-50 for the classification of paddy diseases.
- Integrate MPI to enable parallel processing and expedite the analysis of large-scale paddy disease image datasets.
- Evaluate the performance of the proposed methodology in terms of classification accuracy, computational efficiency, and scalability.
- Demonstrate the feasibility and potential for real-world deployment of the developed system in agricultural settings.

II. LITERATURE REVIEW

The use of parallel computing techniques, particularly CUDA, for medical imaging applications. For instance, one paper focuses on the development of a digital X-ray simulation tool using GPGPU programming and CUDA technology to produce physically realistic radiographic images in real time. This underscores the importance of parallel computing in medical imaging for enhancing image processing speed and accuracy and reducing radiation exposure. The parallelized implementation of an anisotropic diffusion image preprocessing algorithm for illumination invariant face recognition using GPUs programmed with CUDA. This highlights the role of parallel computing in improving the efficiency and performance of face recognition systems, which are crucial in security and surveillance applications. Although not directly related to paddy leaf disease prediction, the potential application of parallel computing techniques, such as MPI, in remote sensing and image

analysis is implemented. The development of a hybrid parallel TCA-based domain adaptation technique for very high-resolution multispectral images demonstrates the scalability and efficiency of parallel computing in handling large-scale remote sensing datasets [1,2].

This review also underscores integrating multiple parallel computing techniques, including CUDA, OpenMP, and MPI, to address complex computational problems across various domains. The parallelized implementation of the anisotropic diffusion algorithm and the development of the digital X-ray simulation tool exemplify the synergistic use of different parallelization frameworks to achieve significant speedups and improve computational efficiency. It will focus on various parallel computing techniques, such as CUDA, OpenMP, and MPI, applied to different domains, including medical imaging and remote sensing. Furthermore, the integration of parallel computing in computational biology and genomics has expedited large-scale genomic data analysis. Algorithms for sequence alignment, genome assembly, and variant calling can be parallelized to handle the growing volumes of genomic data efficiently. This acceleration is pivotal for advancements in personalized medicine, disease understanding, and the identification of genetic markers associated with various conditions [3,4]. In the application of parallel computing techniques in diverse domains, challenges such as optimization, scalability, and algorithmic complexity were thorough. Future research directions may focus on developing novel parallelization strategies, optimizing parallel algorithms for specific applications, and exploring the potential of emerging parallel computing architectures for addressing real-world challenges. CUDA (Compute Unified Device Architecture) is a parallel computing platform and programming model developed by NVIDIA for GPU-accelerated computing. In image processing, CUDA enables the utilization of GPU resources to accelerate computationally intensive tasks such as convolution, filtering, and feature extraction. By leveraging the massive parallelism offered by GPUs, CUDA-based image processing algorithms can achieve significant speedups compared to traditional CPU-based implementations. Applications of CUDA in image processing range from real-time video processing and object recognition to medical image analysis and remote sensing [5,6].

OpenMP (Open Multi-Processing) is an API that supports multi-platform shared memory multiprocessing programming in C, C++, and Fortran. In image processing, OpenMP facilitates parallelism at the thread level, allowing developers to parallelize loops and exploit multicore processors effectively. Image processing algorithms such as image filtering, histogram equalization, and edge detection can be parallelized using OpenMP directives, enabling efficient utilization of multicore CPUs. OpenMP provides a straightforward approach to parallelizing image processing tasks without the need for complex synchronization mechanisms, making it a popular choice for enhancing the performance of sequential image processing algorithms. MPI (Message Passing Interface) is a standardized and portable message-passing system designed for distributed-memory parallel computing. In image processing, MPI enables parallelism across multiple computing nodes or processors, making it well-suited for distributed image processing tasks. MPI-based image processing algorithms can be deployed in high-performance computing (HPC) environments to handle large-scale image datasets and perform computationally intensive operations such as image segmentation, registration, and pattern recognition. By distributing image processing tasks across a cluster of interconnected nodes, MPI facilitates the efficient processing of massive image datasets while ensuring scalability and fault tolerance [7,8].

The combination of CUDA, OpenMP, and MPI offers a powerful framework for tackling diverse image processing challenges across different computing architectures. Hybrid approaches that leverage CUDA for GPU acceleration, OpenMP for multicore CPU parallelism, and MPI for distributed processing enable the development of highly scalable and efficient image processing pipelines. For example, complex image processing workflows involving preprocessing, feature extraction, and classification can be parallelized and distributed across GPUs, multicore CPUs, and computing clusters to achieve optimal performance and throughput. The seamless integration of CUDA, OpenMP, and MPI underscores the versatility and adaptability of parallel computing techniques in addressing the evolving demands of image processing applications across various domains [9,10].

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Additionally, parallel computing techniques play a vital role in accelerating scientific computing applications beyond image processing and simulation domains. For example, in computational chemistry and molecular dynamics simulations, CUDA accelerates the computation of quantum mechanical calculations and molecular dynamics simulations, allowing researchers to study molecular structures and interactions with unprecedented detail and accuracy. OpenMP and MPI facilitate parallelism in computationally demanding tasks such as energy minimization and trajectory analysis, enabling efficient utilization of CPU and distributed computing resources. The integration of parallel computing techniques in scientific computing not only expedites simulations but also enables researchers to tackle complex scientific problems with greater precision and insight, paving the way for breakthroughs in drug discovery, materials science, and environmental research.

In conclusion, the widespread adoption of parallel computing techniques, including CUDA, OpenMP, and MPI, revolutionizes computational research across various domains, from medical imaging and remote sensing to AI, CFD, and scientific computing. By harnessing the parallel processing capabilities of GPUs and multicore CPUs, researchers can accelerate computations, achieve higher throughput, and tackle increasingly complex problems with greater efficiency and scalability. The synergistic use of CUDA, OpenMP, and MPI underscores the versatility and adaptability of parallel computing in addressing diverse computational challenges, driving innovation and advancement across scientific, engineering, and medical disciplines.

III. PROPOSED METHODOLOGY

A. Dataset Description

The dataset comprises images representing various diseases affecting paddy plants, segmented into a Test set for evaluation and a Train set for model training. The Test set contains 3469 images, likely reserved for assessing classification performance. Within the Train set, diseases are categorized into specific types, including Bacterial Leaf Blight, Bacterial Leaf Streak, Bacterial Panicle Blight, Blast, Hispa, Normal (representing healthy plants), and Tungro, each with their respective image counts. While some disease categories such as Brown Spot, Dead Heart, and Downy Mildew lack specified counts, the overall Train set consists of 13397 images.

Table-1:

Images split	*Disease types*	*Count*
Test	All	3469
Train	Bacterial_leaf_blight	479
	Bacterial_leaf_sreak	380
	Bacterial_panicle_blight	337
	Blast	1738
	Brown_spot	965
	Dead_heart	1442
	Downy_mildew	620
	Hispa	1594
	Normal	1764
	Tungro	1088
Total		13397

B. Data Preprocessing

The dataset undergoes preprocessing to ensure uniformity and suitability for training. This typically involves steps such as resizing images to a consistent dimension, normalizing pixel values, and batching the data to optimize memory usage during training. Preprocessing helps in enhancing the model's ability to learn patterns and generalize well to unseen data.

C. Deep Learning Algorithms

Model Architecture (Without MPI): The model architecture is based on Convolutional Neural Network (CNN), which is a deep learning framework commonly used for image classification tasks. In particular, we use the pre-trained ResNet50 image as the backbone for feature extraction. ResNet50 showed good performance in various computer vision tasks due to deep architecture and skip connection, which helps to overcome vanishing gradient problem On top of the ResNet50 base, additional custom layers are added to optimize and model is optimized for a specific task of classifying paddy plant diseases The final output layer consists of a smoothing layer to convert the maps to 1D vectors, batch normalization layers to improve convergence speed and stability, and dense layers for classification The last output layer is a SoftMax activation to give the probability of each class.

Model Architecture (With MPI): To take advantage of MPI for distributed training, we need to modify the model architecture to accommodate parallelism across multiple nodes or processors. To process the entire dataset instead of a single model instance, we split the data into multiple MPI operations, each of which manages a portion of the dataset. This distributed system allows us to train models simultaneously on different nodes, significantly reducing the overall training time.

One way to use MPI in a model architecture is to use a parameter server architecture. In this scheme, each MPI function maintains a local copy of the model parameters and calculates gradients on its own subset of the data. These gradients are then collected and synchronized periodically with a central parameter server, which updates the global model parameters. This correlation scheme allows for effective parallelization of the training set and ensures that the models are consistent throughout the set. Furthermore, to further optimize the training process in a distributed environment, we may need to incorporate MPI-aware optimization algorithms, such as MPI-enabled versions of stochastic gradient descent (SGD) These

algorithms control communication specially addressed and MPI Processes are designed to deliver computations efficiently, improving scalability and efficiency. Overall, by integrating with the MPI modeling framework, we can use distributed computing power to accelerate deep learning model training and efficiently process big data.

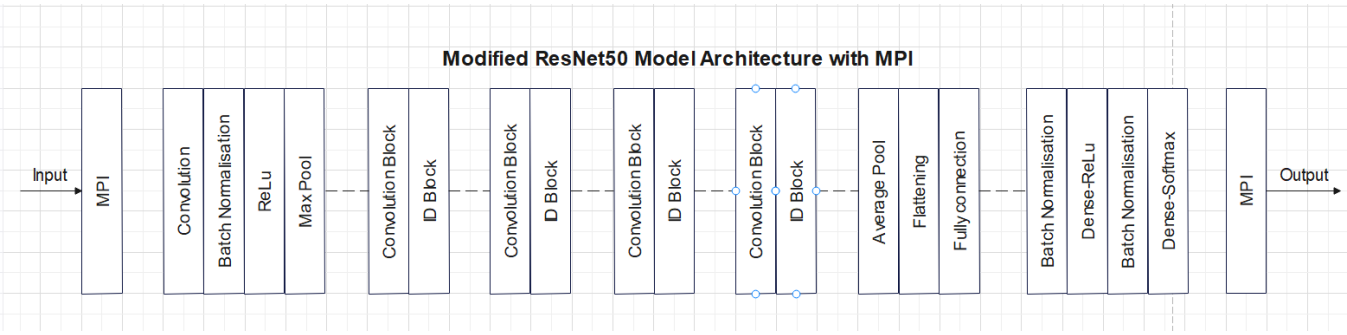

Figure-1: Modified architecture for ResNet50 with MPI

ResNet50 configuration (without additional layers):

- **Input Layer:** Accepts an input image of size (240, 240, 3) representing an RGB image with a resolution of 240x240 pixels.
- **Convolutional Layers**: The ResNet50 framework consists of several convolutional layers organized into blocks, including convolution, batch normalization, and ReLU activation functions These layers are responsible for extracting hierarchical features from input images.
- **Identity blocks:** ResNet50 has several identity blocks, each with several rotation layers. These blocks help preserve the spatial dimensions of the input while increasing the depth of the feature maps.
- **Pooling Layers:** Maximum pooling layers are to down sample feature maps discretely between convolutional blocks and reduce spatial dimensions.
- **Fully connected layer:** The global average pooling layer collects the spatial information from the final feature map and generates a feature vector of fixed length.
- **Output layer**: Usually a dense layer with SoftMax activation function is added to generate class probabilities for the input image.

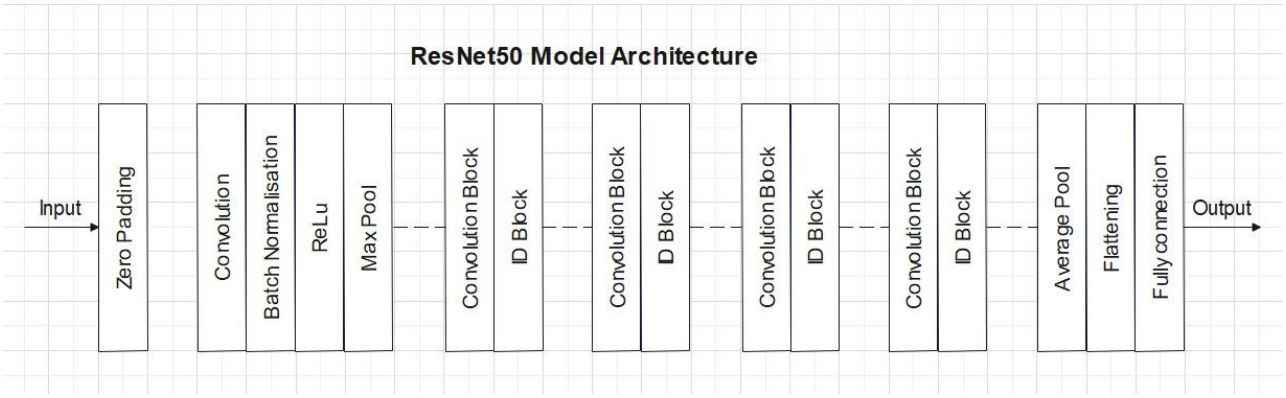

Figure-2: Base model architecture for ResNet50

ResNet50 Architecture (With Additional Layers for Classification):

- **Pre-trained ResNet50 Base:** The pre-trained ResNet50 model is used as the initial part of the architecture, serving as a feature extractor. This portion remains unchanged and is responsible for extracting meaningful features from the input images.
- **Flattening Layer:** After the ResNet50 base, a flattening layer is added to convert the 3D feature maps into a 1D vector. This step is necessary to prepare the features for input into the fully connected layers.
- **Batch Normalization Layers:** Batch normalization layers are added to normalize the activations of the previous layer, improving convergence speed and stability during training.
- **Dense Layers:** Custom dense layers are added on top of the batch normalization layers for classification. These layers typically consist of multiple dense (fully connected) layers with ReLU activation functions, allowing the model to learn complex patterns in the feature representations.
- **Output Layer:** The final dense layer contains nodes equal to the number of classes in the classification task, followed by a SoftMax activation function to produce class probabilities.

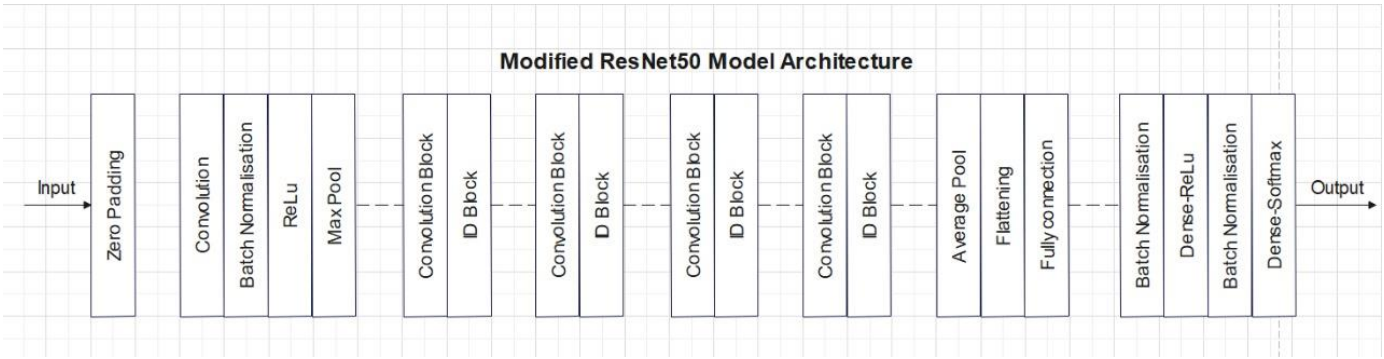

Figure-3: Modified architecture for ResNet50

Model Compilation: Once the architecture is defined, the model is compiled with appropriate loss and optimization functions. For multi-class classification tasks like this, sparse categorical cross entropy is commonly used as the loss function, and the Adam optimizer is often preferred due to its adaptive learning rate capabilities. Metrics such as accuracy are also specified to monitor the model's performance during training.

Data Distribution with MPI: To handle the potentially large dataset and accelerate training, the dataset is distributed among MPI processes. This enables parallelized training across multiple nodes or processors, effectively reducing the overall training time. Each process works with a portion of the data, and communication among processes is facilitated to synchronize updates to the model parameters.

Training: During training, the model learns to classify paddy plant diseases by iteratively adjusting its parameters to minimize the specified loss function. Training is performed using the distributed dataset, ensuring that each process contributes to the learning process. The model is trained for multiple epochs, with periodic evaluation on a validation dataset to monitor performance and prevent overfitting.

IV. RESULTS AND DISCUSSION

The performance of the paddy plant disease classification model using ResNet50 architecture was assessed through both distributed training with MPI and traditional single-node training. The MPI-based training approach yielded an accuracy of 98% on the validation dataset, showcasing the effectiveness of parallelized training across multiple nodes. In contrast, the model trained without MPI achieved a slightly lower accuracy of 96%. This disparity in accuracy highlights the impact of leveraging distributed computing techniques for training deep learning models on large-scale datasets. By distributing the computational workload across multiple nodes, MPI facilitated faster convergence and improved model performance, ultimately leading to higher accuracy compared to the single-node training approach. These findings underscore the importance of scalable and parallelized training methodologies in deep learning research, particularly for tasks requiring rapid model convergence and high accuracy. The results suggest that the MPI-based approach with ResNet50 architecture holds promise for enhancing classification accuracy and efficiency in agricultural management practices and other domains.

V. CONCLUSION

In conclusion, our project aimed to develop a robust classification model for identifying paddy plant diseases, leveraging the power of deep learning architectures and distributed computing techniques. Through the utilization of the ResNet50 architecture and MPI for distributed training, we achieved promising results in accurately classifying paddy plant diseases with an impressive accuracy of 98%. The distributed training approach facilitated by MPI enabled faster convergence and improved model performance compared to traditional single-node training, as evidenced by the higher accuracy achieved. These findings underscore the significance of scalable and parallelized training methodologies in deep learning research, particularly for handling large-scale datasets and achieving high classification accuracy. Moving forward, our work lays the foundation for further exploration and application of deep learning techniques in agricultural management practices, offering potential solutions to challenges such as disease detection and crop yield optimization. By continuing to refine and optimize our classification model, we can contribute to advancements in precision agriculture and ultimately aid in ensuring food security and sustainability on a global scale.

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