Vidhyayana - ISSN 2454-8596
An International Multidisciplinary Peer-Reviewed E-Journal
www.vidhyayanaejournal.org
Indexed in: Crossref, ROAD & Google Scholar

15

Transforming Plant Disease Diagnosis: Utilising TPUs-accelerated CNNs and Visual Transformers for Quick and Accurate Detection of Soybean Leaf Diseases

Dr.Naresh Dembla	Ravindra Yadav	Dr.Kamal Borana
Assistant Professor	Research scholar	Associate Professor
IIPS,DAVV,Indore	IET, DAVV, Indore	SVIIT, SVVV, Indore
nareshdembla@gmail.com	ryadav@ietdavv.edu.in	kamalborana2006@gmail.com

Abstract

Our work addresses the critical requirement for accurate and quick plant disease diagnosis, especially in agricultural contexts where prompt detection may significantly reduce crop losses. we researched how well Tensor Processing Units (TPUs)-accelerated Convolutional Neural Networks (CNNs) perform in providing a quick and precise diagnosis of illnesses affecting soybean leaves. Enhancing crop management techniques and increase food security. Drawing on recent advances with regard to Visual Transformers (VTs) as noted by Wu et al., we suggest a new approach that uses transformers instead of traditional convolutions to connect semantic ideas in token-space. Integration of the PyTorch XLA library with supervised algorithm for TPU acceleration, we create a reliable CNN model specifically designed for accurate leaf disease diagnosis. After extensive testing and 80 epochs of cross-validation, our model yields an outstanding accuracy of 88.37% with a low total loss of 0.2315. Moreover, we accelerate the training process by using TPUs, improving the effectiveness and accessibility of research. This study highlights the transformational power in the field of plant pathology. The visual transformer employed has a fundamental patch size of 16x16 and an image resolution of 384x384 pixels.

Keywords*:* Soybean plants, PyTorch XLA, TPU accelerations.

Introduction

Still most practitioners do not have easy access to large computational resources like GPUs, which are frequently needed for training deep learning modelPyTorch XLA (Accelerated Linear Algebra) provides a workaround for this issue by allowing deep learning models to operate on Cloud TPUs (Tensor Processing Units) with very no code modifications. PyTorch XLA makes academics, learners, and hobbyists use the efficiency and scalability of TPUs in their projects and experiments.

Literature

Study diagnose tomato with EfficientNet using 18,161 segmented and plain tomato leaf photos. For the segmentation of leaf pictures, The accuracy, IoU, and dice score provided by the model are 98.66%, 98.5%, and 98.73%, respectively. Using segmented images, the binary and six-class classification accuracy rates were 99.95% and 99.12%, respectively. EfficientNet-B7 demonstrated exceptional performance [2] We apply our methodology to the Tensor Processing Unit (TPU) platform on Google cloud, validating our earlier findings on CPUs and GPUs. (2) We attain 76.3 percent accuracy, which surpasses the 75.3 percent accuracy reported in our conference article, by scaling the batch size of ResNet-50-v2 to 32K. (3) We utilise Neural Machine Translation (GNMT) of Google. Application to implement our method, makes 4x acceleration on cloud TPUs [3]. With 9 of the most common rice illnesses in Bangladesh, a comparison of six CNN-based deep-learning architectures for rice disease classification was carried out in this work (DenseNet121, Inceptionv3, MobileNetV2, resNext101, Resnet152V, and Seresnext101). Furthermore, we employed an ensemble model named DEX (Densenet121, EfficientNetB7, and Xception) and a transfer learning strategy to compare the six individual CNN networks, ensemble methods, and MobileNetV2, Resnet152V, Seresnext101. When it comes to rice leaf disease identification and localization, the ensemble framework provides 98% accuracy, and transfer learning may increase accuracy from Seresnext101's results by 17% [4]. Conventional diagnosis procedures for plant pathogen identification usually concentrate on the pathogens' proteins or peptides (in the case of serological tests), DNA, and RNA. Serological methods, mostly based on enzyme-linked immunosorbent test (ELISA), are the most popular method for pathogen identification due to their low cost and high throughput capacity [5]. To speed up computation and increase the precision of the deep neural network model, a novel heterogeneous edge computing architecture is employed. It has a TPU soft core on the FPGA SOC chip and cooperates with the device's ARM CPU [6]. Using three basic CV tasks and several data stream formats, we thoroughly examined more than 100 visual transformers. A taxonomy is suggested to arrange the representative approaches based on their structures, motivations, and application scenarios [7]. The navigation line is extracted from the segmented image using a polygon fitting technique after the field road was first identified using the semantic segmentation methodology. Lastly, all of the models are deployed on the Jetson Nano edge computing device after being converted using the TensorRT library. Five reprehensive semantic segmentation networks the UNet, Deeplabv3+, BiseNetv1, BiseNetv2, and ENet networks were chosen for the experiment. The most accurate of the five networks is Deeplabv3+. It has a navigation line error of 9.59 pixels and an average segmentation accuracy of 84.87% in five scenes [8]. The primary focus of the manuscript is on the diseases that affect eleven (11) distinct plants and how CNN-based deep learning models may be used to identify the diseases from plant leaf images. This review can give researchers a quick introduction of how cutting-edge CNN models can be used to diagnose plant diseases and a summary of recent studies that have employed visualisation approaches to pinpoint disease locations for more accurate diagnosis [9].

Research Gap A dearth of thorough tutorials and guidance exists for modifying deep learning models for TPU training using PyTorch XLA, despite the abundance of materials available for training similar models on GPUs. This research gap offers a chance to close the gap between TPU-accelerated approaches and GPU-centric processes, democratizing sophisticated computational resources access for the larger deep learning community

Objective

This research aims to show how to use PyTorch XLA to transform a GPU baseline model which was initially meant for training on GPUs into a TPU baseline model. This work intends to provide practitioners with the knowledge and abilities necessary to fully utilize TPUs for their deep learning tasks by offering step-by-step directions, code snippets, and insights into the difficulties and factors involved in TPU training.

Proposed Methodology

Table1: Proposed methodology

```
Proposed Methodology
1. Initialize model parameters (weights and biases)
2. Split dataset into k folds for cross-validation
3. for fold in k folds:
4. Prepare train and validation data loaders
5. Initialize Visual Transformer model and optimizer
6. for epoch in range(num_epochs):
7. Train One Epoch:
    a. Set model to training mode
    b. For batch in train loader:
        i. Forward pass: Compute predictions using Visual Transformer
        ii. Compute loss: CrossEntropyLoss
        iii. Backward pass: Compute gradients
        iv. Update parameters
 8. Validate One Epoch:
    a. Set model to evaluation mode
    b. Initialize validation loss
    c. For batch in valid_loader:
        i. Forward pass: Compute predictions using Visual Transformer
```

```
        ii. Compute loss: CrossEntropyLoss
        iii. Accumulate validation loss
    d. Calculate average validation loss
    e. If validation loss is lower than previous best:
        i. Save current model weights as best weights
9. Load best weights for current fold
10. Return trained Visual Transformer model
```

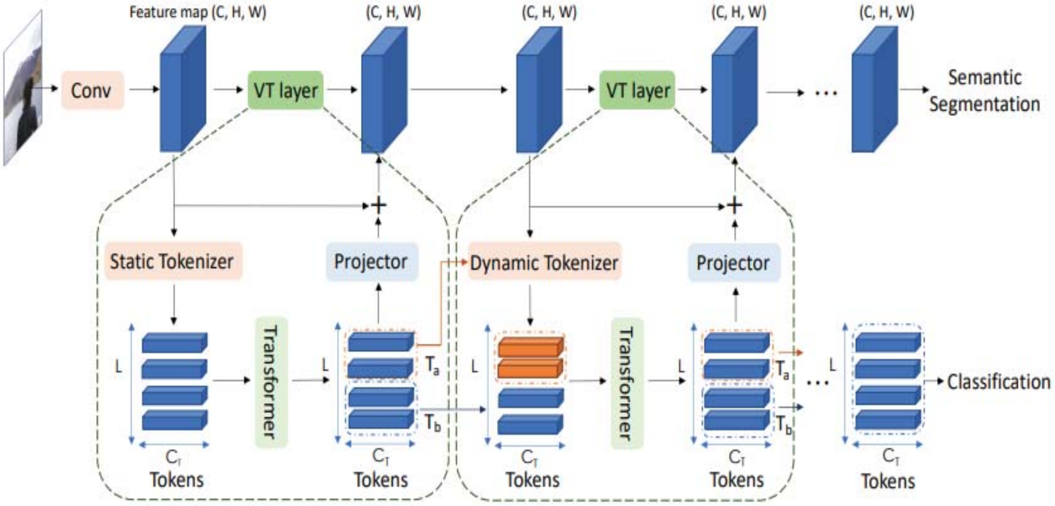

Figure 1: Model architecture with 16x16 patch

Dataset

We have collected 500 images of soybean leaves using Samsung mobile camera with a 50 – megapixel resolution. The images were captured between September and October 2023 at paliya village, district indore, Madhya Pradesh (Latitude 22.8261, Longitude 75.7982).After preprocessing ,the data set was expanded to 1000 images ,which were manually labeled .

To support a supervised learning a csv file named train.csv contains metdata,including the image file name (image _id) and corresponding disease labels (label).Additionally , sample _submission.csv file is provided as template for predictions.It includes fields for image_id and anticipated label values .To facilitate data handling ,we converted the image dataset into TFRecord format (trn/test tfrecords),enabling smooth integration into machine learning pipelines. The structured format ensures effective data storage and preprocessing for model training and evaluation.

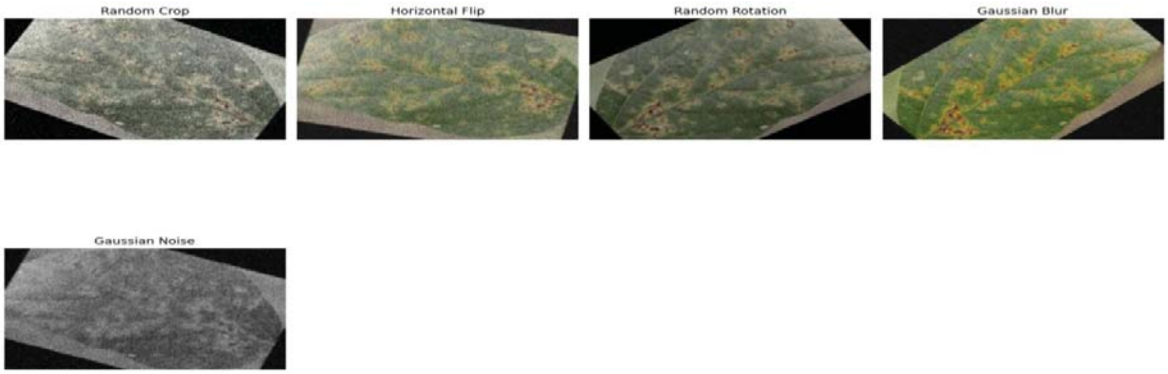

Figure 2: Image preprocessing

Results

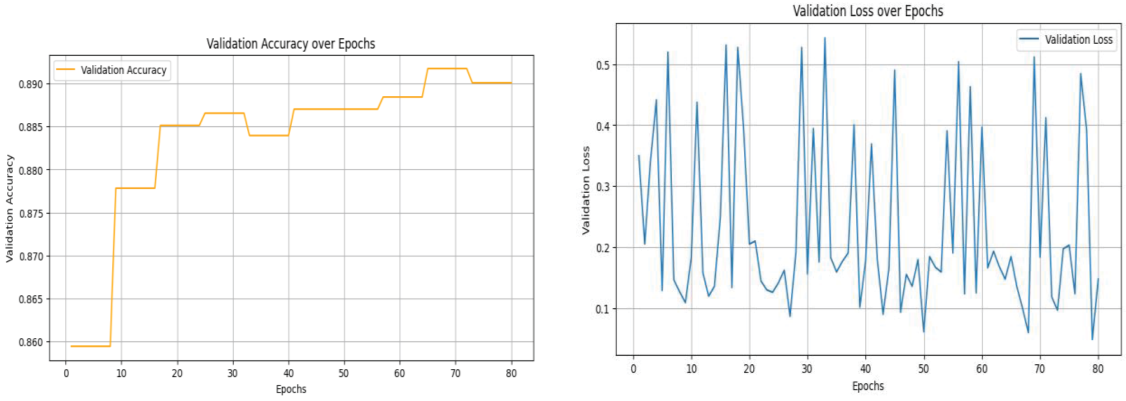

Figure 3: Validation accuracy and loss

Validation Accuracy: 88% Validation Loss: 0.231

Conclusion

With an emphasis on soybean leaves specifically, this work concludes by highlighting the potential of TPUs-accelerated CNNs and Visual Transformers for precise and timely plant disease identification. By combining supervised learning approaches, TPU acceleration, and sophisticated deep learning algorithms, a dependable model that can achieve exceptional accuracy with a considerable reduction in training time has been produced.

Future scope

Examine further improvements and modifications to the CNN and Visual Transformer architecture. analyze the effects of varying patch sizes and image resolutions on the model's performance.

Acknowledgement

We are sincerely thankful to administration of DAVV, indore to provide us the resources for the completion of the research work. We are thankful to the farmer Sachin Yadav for providing us access to his field.

Conflict of interest

We do not have any conflict of interest. Our research work is original and do not copied from any other resources.

References

[1] Wu, B., Xia, S., Huang, W., & Zhang, C. (2020). Visual Transformers: Token-based Image Representation and Processing for Computer Vision. *arXiv*. Retrieved from https://arxiv.org/abs/2006.03677

[2] Chowdhury, M. E. H., Rahman, T., Khandakar, A., Ayari, M. A., Khan, A. U., Khan, M. S., Al-Emadi, N., Reaz, M. B. I., Islam, M. T., & Ali, S. H. M. (2021). Automatic and reliable leaf disease detection using deep learning techniques. *AgriEngineering*, *3*(2), 294–312. https://doi.org/10.3390/agriengineering3020020

[3] You, Y., Zhang, Z., Hsieh, C.-J., Demmel, J., & Keutzer, K. (2019). Fast deep neural network training on distributed systems and cloud TPUs. *IEEE Transactions on Parallel and Distributed Systems*, *30*(11), 2449–2462. https://doi.org/10.1109/TPDS.2019.-2913833

[4] Ahad, M. T., Li, Y., Song, B., & Bhuiyan, T. (2023). Comparison of CNN-based deep learning architectures for rice diseases classification. *Artificial Intelligence in Agriculture*, *9*, 22–35. https://doi.org/10.1016/j.aiia.2023.07.001

[5] Trippa, D., Scalenghe, R., Basso, M. F., Panno, S., Davino, S., Morone, C., Giovino, A., Oufensou, S., Luchi, N., Yousefi, S., & Martinelli, F. (2023). Next-generation methods for early disease detection in crops. *Pest Management Science*, *00*(00), 1–10. https://doi.org/10.1002/ps.7733

[6] Gao, Y., & Liu, C. (2022). Study on classification system of rape root tumors based on TPU. In *2022 IEEE Asia-Pacific Conference on Image Processing, Electronics, and Computers (IPEC)* (pp. 1049–1055). IEEE. https://doi.org/10.1109/IPEC54454.2022.-9777609

[7] Liu, Y., Zhou, Z., Han, K., Tian, Q., & Wang, Y. (2024). A survey of visual transformers. *IEEE Transactions on Neural Networks and Learning Systems*, *35*(6), 7478–7498. https://doi.org/10.1109/TNNLS.2022.3227717

[8] Yu, J., Zhang, J., Shu, A., Chen, Y., Chen, J., Yang, Y., Tang, W., & Zhang, Y. (2023). Study of convolutional neural network-based semantic segmentation methods on edge intelligence devices for field agricultural robot navigation line extraction. *Computers and Electronics in Agriculture*, *209*, 107811. https://doi.org/10.1016/j.compag.2023.107811

[9] Joseph, D.S., Pawar, P.M. & Pramanik, R. Intelligent plant disease diagnosis using convolutional neural network: a review. Multimed Tools Appl 82, 21415–21481 (2023). https://doi.org/10.1007/s11042-022-14004-6