An Instance-based Deep Transfer Learning Approach for Resource-Constrained Environments

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ABSTRACT

Although Deep Learning (DL) is revolutionising practices across fields, it requires a large amount of data and computing resources, requires considerable training time, and is thus expensive. This study proposes a transfer learning approach by adopting a simplified version of a standard Convolution Neural Network (CNN), which is successful in another domain. We explored three transfer learning approaches: freezing all layers except the first and the last layer of the CNN model, which we had modified, freezing the first layer, updating the weights of the rest of the layers, and fine-tuning the entire network. Furthermore, we trained a DL model from scratch to act as a baseline. We performed the experiments on the Edge Impulse platform. We evaluated the models based on plant-village, tea diseases and land use datasets. Fine-tuning and training the whole network produced the best precision, accuracy, recall, f-measure and sensitivity across the datasets. All three transfer learning schemes significantly reduced the training by more than half. Further, we deployed the fine-tuned model in detecting diseases in tea two months after the idea's conception, and it showed a good correlation with the experts' decisions. The evaluation results showed that it is viable to perform transfer learning among domains to accelerate solutions deployments. Additionally, Edge Impulse is ideal in resource-constrained environments, especially in developing countries lacking computing resources and expertise to train DL models from scratch. This insight can propel the development and rollout of various applications addressing the Sustainable Development Goals targeted at zero hunger and no poverty, among other goals.

CCS CONCEPTS

• **Computing methodologies → Instance-based learning**; **Computer vision**.

KEYWORDS

machine learning, transfer learning, convolution neural network, edge impulse

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1 INTRODUCTION

Deep Learning (DL) is a branch of Machine Learning (ML) that is currently considered an enabling technology for the industrial 4.0 revolution [12]. The technique aims at simulating the mechanism of learning that is done by biological counterparts [1] by implementing neurons in humans through computational units connected with weights. The learning process in DL takes place when weights are updated based on the runs made by the model by sensing patterns in data [5, 29]. The input layer receives data while convolution layers apply filters to the input for features to be effectively detected [8]. The pooling layer reduces feature sensitivity, resulting in a more generalized structure. The activation layer develops the ability to learn something complex and intriguing by applying mathematical functions $f(x)$ to the input layer. The dropout layer removes specific random input values, resulting in a comprehensive dataset that avoids over-fitting. Finally, the output layer produces results devised by the neural network [30].

Transfer learning (TL) is adopting an ML model trained for a particular task in a new but comparable task. This may be due to the lack of a large dataset in the new domain, the need for accelerated deployment and the lack of computing resources to perform training from scratch [26].

Edge Impulse[1] is a cloud-based platform that provides services for building machine learning models for TinyML-enabled edge devices. It aims at delivering computing resources to developers at no cost, supporting the building of ML models for resource-constrained devices, accelerating deployments of ML models, building explainable ML models, and simplifying the process of training machine learners [35]. We implemented our models in this platform to test their feasibility and applicability in resource-constrained devices and it took two months from the idea conception to the actual deployment in a tea farm which was accelerated.

Among the 17 sustainable development goals for developed and developing countries are: no poverty and zero hanger. Ending poverty ensures that resources are available to people across various environments and countries. At the same time, zero hunger

[1] https://www.edgeimpulse.com/

aims to provide food security and improved nutrition and promote sustainable agriculture. This study aims at contributing to these goals by proposing a transfer learning approach for classifying land use, pests and diseases in tomatoes, potatoes and tea to improve yields in these crops and also ensure proper land management. The proposed model has been offloaded to run on a mobile phone and evaluated in actual deployment to detect tea sickness in a tea farm in Koiwa location, Bomet County, Kenya.

1.1 Problem Statement

Although DL shows immense capabilities in various domains, it suffers several challenges. These challenges include the need for a large amount of data to learn [20], it is demanding in terms of computing resources [28], requires a lot of skills, and the development process takes time and is often a black box process. Computing resources are still constrained in many countries, especially in developing countries [2, 25] and with deep learning being resource-hungry, running them in these environments becomes a challenge[7, 24]. Thus, most researchers in developing countries are not able to implement them [6, 11]. This is a significant problem, as entrepreneurship and innovative solutions across all 17 Sustainable Development Goals are hindered. Our objective is to show-case a practical and accelerated deployment of a solution, employing the Edge Impulse environment with three different datasets and application scenarios: a landuse dataset to access different land usages especially in developing countries, a plant village image dataset to implement a sickness recognition in plants and tea leaves dataset to detect diseases in tea leaves.

1.2 Contributions

This research proposes to address the challenges that we identified in Section 1.1 by performing a transfer learning on a deep learner that proved sophisticated during its application in the detection of optimum fermentation of black tea. We implemented the solution in an Edge Impulse platform, allowing us to use the available computing resources and speed up transfer learning. The contribution of this study can be summarised as follows:

- A transfer learning approach for resource-constrained environments has been proposed.
- We performed the experiments in an Edge Impulse cloud platform which was available at no cost and ensured the accelerated deployment of the solution as it took two months from the idea's inception to real-deployment of the solution.
- The model which underwent fine-tuning and training has been evaluated in an actual deployment to detect tea sickness.

The rest of the paper is organized as follows: Section 2 provides the related work. Section 3 describes the Convolutional Neural Networks(CNN) model adopted and the rationale for its selection. We describe the methodology in Section 4 and the evaluation results in Section 5. We provide discussions and lessons learnt in section 6, we conclude and propose future work in Section 7.

2 RELATED WORK

In this section, we give a short overview of recent related works. This list is not intended to be exhaustive or complete, but to give an overview of the state of the art. Transfer learning has been widely adopted in the last few years as it greatly improves the learning performance on reduced datasets, thus avoiding time expensive data labelling efforts. Furthermore, it accelerates the deployment of proposed models [26]. Research in [9] adopted transfer learning on VGG16 standard ML model for application in the detection of mildew diseases in millet. Researchers in [27] performed transfer learning on the following standard ML models VGGNet, ResNet, and Xception for the identification and detection of diseases in tea. Further, researchers in [34] performed transfer learning on VGG16 ML to identify hot pepper diseases in plants. Most of these reported studies attempted to detect pests and diseases in plants while adopting standard ML models for transfer learning.

The high population growth is a serious concern, mainly due to limited resources globally and more so in developing countries [31]. Consequently, researchers in the field have been proposing computing techniques for monitoring land-use. Authors in [23] performed a feasibility study on the application of transfer learning on VGGG and Wide Residual Networks (WRNS) standard ML models for land-cover and land-use classification. Researchers in [3] explored Resnet50V2, InceptionV3, and VGG19 for use in the classification of vegetation images captured using a satellite. The literature shows that transfer learning is being considered for the accelerated development of ML models since it simplifies the process of training, validation and testing. However, most of these models adopted the standard ML models, resulting in longer training times. To the best of our knowledge, the current study is the first attempt at adopting a simplified version of a deep learner for accelerated development and deployment of solutions.

3 CNN MODEL

Several standard ML models exist for performing transfer learning, including VGG[4] Inception Model [10], and ResNet Model [15]. However, in this study, we adopted a simplified version of the AlexNet model [4] dubbed TeaNet because of the following reasons: first, since the TeaNet model is a reduced version of the AlexNet model; we expected it to train faster than "standard" ML models as it had fewer parameters for training. Second, in our previous study [19], we trained TeaNet using two distinct datasets with similar features to the current datasets. Third, we deployed the model with the Internet of Things to monitor tea fermentation [16, 17] and showed much promise. The network architecture of the model is illustrated in Fig 1.

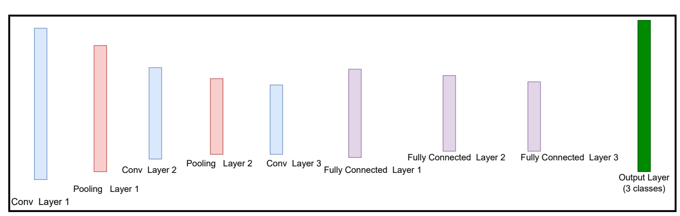

Figure 1: The TeaNet architecture proposed for real-time monitoring of tea fermentation in [17]

4 METHODOLOGY AND PROPOSED METHODS

This section discusses the datasets selected, the transfer learning approach, the implementation environment, and the performance evaluation metrics.

4.1 Selection of Datasets

We have examined various datasets and we decided on two, namely plant-village dataset [22] and land-use dataset [14, 33]. We chose the datasets to demonstrate the broad applicability of our approach. These datasets have been selected as standard datasets in Kaggle contests [33]. Furthermore, we collected a tea diseases dataset [18] and used it to train, validate and evaluate the model. The dataset contained eight classes of tea diseases (Fig 2.)

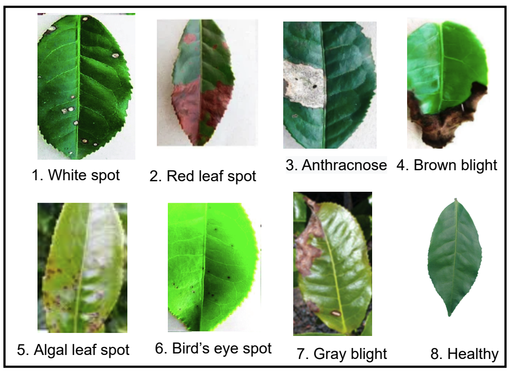

Figure 2: Example of each class of images of tea sickness dataset that was used in the study

In the experiments, we used 100 images of each dataset. The images were divided into the following categories: training, validation, and testing sets with 70%, 10%, and 20%, respectively. Thus, 70 images for training, 10 for validation, and 20 for testing were selected for every dataset. Note the very low number of required images: the original TeaNet training set consisted of 6,000 images.

4.2 Transfer learning Approach

We used a pre-trained Deep Convolutional Neural Network (DCNN) model dubbed TeaNet discussed in Section 3. The model was trained using the plant-village, tea diseases and land-use datasets as mentioned in Section 4.1. We cut the first and last layer of the TeaNet model, then affix an input layer and one dense layer (fully connected layer), which had eight output nodes since we had eight different output classes (Fig. 3).

We followed three approaches when performing transfer learning on the model as proposed in [27]. In the first approach, we froze all layers except that we modified and performed fine-tuning to the transferred layers. We referred to this as T_a. In the second approach, the first layer of the network is frozen, and the weights of the rest of the network were updated, and this scheme was denoted as T_b. Further, we conducted fine-tuning and training on the whole network, which we represent as T_c. Finally, we trained the DCNN from scratch and denoted it as T_d to act as a baseline.

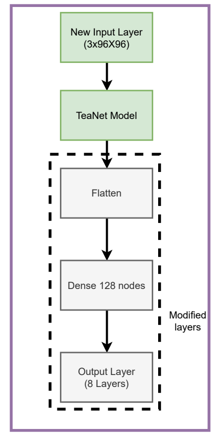

Figure 3: The proposed transfer learning approach adopted in this study

4.3 Implementation Environment

We adopted Edge Impulse [1] as it is ideal for transfer learning tasks and is available to developers at no cost [32]. Further, the deployment of solutions implemented in this platform is accelerated and can be easily offloaded to resource-constrained devices including mobile phones [21]. After creating an account, we first loaded TeaNet into the Edge Impulse cloud environment and the new images of one of our datasets and specified the training, validation, and testing ratio. Then, we defined the exact TL schene to use (T_a through T_d) and let Edge Impulse perform the training (Fig4). After training, the platform tested and visualised the results in a table. We could now use the trained model to send a classification request with new images from the smartphone.

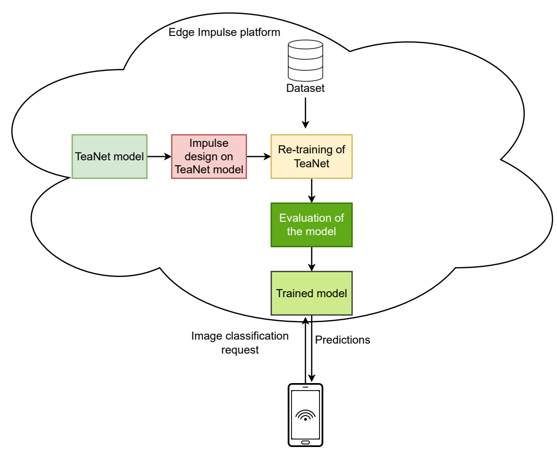

Figure 4: Illustration of how transfer learning was implemented in the Edge Impulse platform

[1] https://edgeimpulse.com/

4.4 Evaluation Metrics

We evaluated the models based on precision, recall, accuracy, f-measure, and sensitivity [13].

5 EVALUATION RESULTS

Fig 5 shows the progression of training losses for T_a (fine-tuning only the transferred layers), T_b (freezing the first layer of the model and updating the rest), T_c (fine-tuning of the whole network), and T_d (training from scratch) during training using the land-use dataset. T_a, T_b, and T_c converged faster than T_d since their layers have some parameters and thus did not require training from scratch. On the other hand, training from scratch took the longest time because initially, the parameters of the layers were not updated; thus, it took time to learn. The same observation was made when the models were being trained using the other datasets.

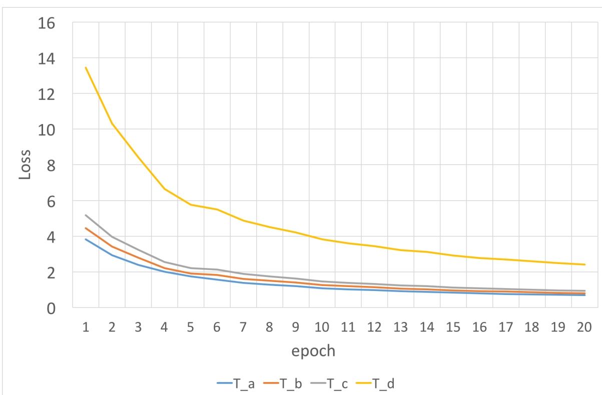

Figure 5: Training loss of training only modified layers (T_a), training all layers except the input layer (T_b), full fine-tuning and training (T_c), and training from scratch (T_d) on the land-use dataset.

The average time required for training per epoch is illustrated in Fig 6. Training from scratch (T_d) took the highest time to run an epoch since the model learned weight initialization from scratch. Generally, transfer learning took less time to train since it had fewer parameters for fine-tuning. This is particularly evident in T_a, where only the weights of the appended layers were modified. The average training time for each epoch was reduced by more than 50% when transfer learning was adopted. Further, T_b and T_c required almost similar training times. Most importantly, all the transfer learning schemes took less training time compared to results presented by authors in [27] who adopted a standard DCNN. These results confirmed that adopting simplified versions of these standard DCNN results in fewer training times since they have fewer parameters for fine-tuning.

We evaluated the models based on precision, recall and f-measure using the land use, plant village and tea diseases dataset and presented the results in Fig. 7. Fine-tuning and training the entire CNN network produced the best results across the metrics: precision, recall, and f-measure. Most importantly, fine-tuning and training the CNN as a whole network had an accuracy of 0.8676; thus, the

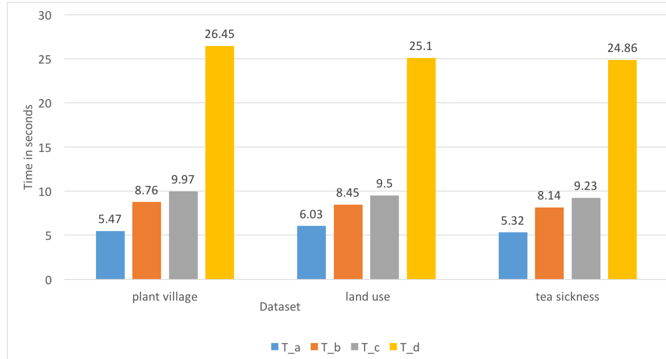

Figure 6: Average training times of only modified layers (T_a), training all layers except the input layer (T_b), full fine-tuning and training (T_c), and training from scratch (T_d) for each epoch.

model's probability of having accurate results was 86.76%. Training the model from scratch(T_d) recorded the second-best results while training all layers except the input layer (T_b) produced the third-best results. Training only modified layers of the network (T_a) recorded the least results across the metrics. However, all the models showed good classification performance across the metrics.

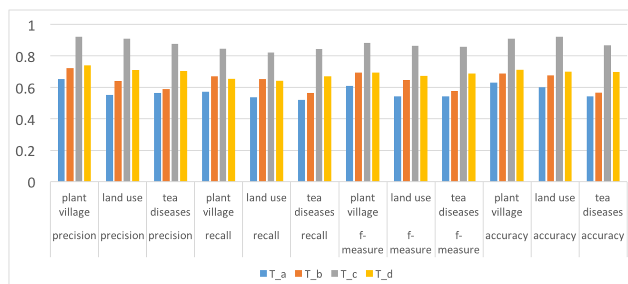

Figure 7: Comparison of the performance of training only modified layers (T_a), training all layers except the input layer (T_b), full fine-tuning and training (T_c), and training from scratch (T_d).

The confusion matrix for the model T_c (transfer learning and full fine-tuning) across classes of tea leaves dataset is presented in Table 1. The model showed good performances across the dataset classes, with the minor sensitivity achieved at 75% in class gray blight while confusing 2 of the images in this class to belong to class red leaf spot and brown blight. The model produced the best sensitivity in class Anthracnose since the image symptoms of this sickness were distinct from the diseases in the other classes. The results confirmed that the TeaNet model was appropriate for transfer learning in this task.

Table 1: Confusion matrix of T_c (transfer learning and full fine-tuning) across classes of tea leaves dataset

class	*Red leaf spot*	*Algal leaf spot*	*Bird's eye spot*	*Gray blight*	*White spot*	*Anthracnose*	*Brown blight*	*Healthy*	*sensitivity*
Red leaf spot	**16**	2	0	0	2	0	0	0	**80%**
Algal leaf spot	0	**17**	0	1	0	0	1	1	**85%**
Bird's eye spot	0	0	**18**	0	2	0	0	0	**90%**
Gray blight	2	1	0	**15**	0	0	2	0	**75%**
White spot	0	0	3	0	**17**	0	0	0	**85%**
Anthracnose	0	1	0	0	0	**19**	0	0	**95%**
Brown blight	2	0	0	1	0	0	**17**	0	**85%**
Healthy	1	0	0	1	0	0	0	**18**	**90%**

5.1 Deployment of the model in a tea plantation

After showing promising results in the simulation environment, we offloaded model T_c (transfer learning and full fine-tuning) to a mobile phone. We adopted it in actual deployment to detect tea diseases in a tea farm in Koiwa, Bomet county, Kenya, between 21st March 2022 and 26th March 2022. Users took images of tea leaves using their mobile phones, and the model predicted their corresponding class (Fig 8).

Figure 8: Tea farmers detecting diseases in tea leaves using T_c (transfer learning and full fine-tuning) model on a farm in Koiwa, Bomet county, Kenya.

The performance of model T_c (transfer learning and full fine-tuning) during deployment is presented in Fig 9. The minimum precision and accuracy values were 0.7954 and 0.7885 on 9th April 2022. These low values could be because the weather was gloomy, and thus the images taken by the mobile phone camera were not clear. These results implied that the probability of the model's correct prediction was always more than 78%. Generally, the model showed good classification performance throughout the other days. However, the model's performance was reduced when deployed compared to its evaluation in offline mode. This could be due to background noise, and the capabilities of the mobile devices' cameras during deployment affected the performance. The farmers could have been inaccurate in taking tea pictures and thus may require training.

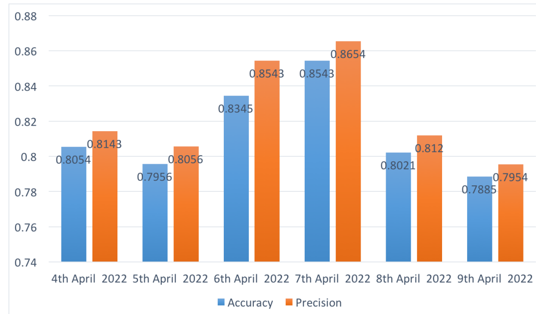

Figure 9: Precision and accuracy of model T_C (transfer learning and full fine-tuning) during its deployment on a tea farm in Koiwa, Bomet county, Kenya.

6 DISCUSSIONS AND LESSONS LEARNT

This study has explored three transfer learning approaches for accelerated deployments of solutions implemented in an Edge Impulse platform. We adopted the TeaNet DCNN model, a simplified version of the classical AlexNet model. We trained, validated and evaluated the schemes using land use, plant village and tea leave datasets. All the three transfer learning schemes converged faster than training from scratch since their layers had some knowledge. Thus with transfer learning, training of ML models was accelerated and therefore resulted in the reduction in training time by more than 50%. Although this reduced training time could have resulted in decreased energy consumption by the devices, we could not ascertain the amount saved as we performed all the experiments in the edge impulse platform where this information was unavailable.

Furthermore, fine-tuning and training the whole network produced the best precision, recall, f-measure, and accuracy results. We further confirmed its stability in a confusion matrix where it recorded stable results across the classes of each dataset. Generally, all the other two training schemes also showed promising results. Any training scheme can be adopted, but a trade-off is to be made on the performance requirements and time available for training.

Challenges remain to make this or a similar approach well suited for developing countries. First, some level of expertise for fine-tuning the models is still required. Our recommendation would be to work on training materials to enable faster methodology adoption. Second, an internet connection is required for classifying the images, which might be a significant drawback when rolling out the applications later. We recommend downloading the trained model in a compressed way to the smartphone directly. Third, a developer must find a suitable model for applying transfer learning - some are already available. Still, the community is responsible for making more of them readily available to increase the impact. Fourth, it requires considerable programming knowledge to implement the trained model on other computing platforms. This halts the accelerated deployments of these solutions. Our recommendation would be for Edge Impulse to have ready interfaces which researchers can use to connect with their platforms.

7 CONCLUSION AND FUTURE WORK

Our study highlights that various transfer learning schemes produced varying performances. We found that adopting a DCNN and performing fine-tuning in the whole network had stable results. Freezing all networks except the modified layers promised to be the most unstable approach. However, freezing the first layer of the DCNN and updating the weights of the rest of the network produces as good results as training a model from scratch. Nevertheless, there is no ground truth on which approach to follow, but a trade-off between the accuracy, training time, and computing resources must be made. This study also highlights that adopting a simplified version of a standard DCNN to perform transfer learning results in lesser training times since the parameters are fewer and thus appropriate for accelerated deployments and the reduction in the energy consumption.

Further adopting the Edge Impulse platform to perform training of deep learners is a viable approach and ensured that the solution was deployed two months from its conception, which was accelerated. This is encouraging and significant when there is a need to expedite the deliverance of solutions.

During the model deployment, its performance was reduced because some of the captured images contained noise; some were not clear depending on the weather and time of the day. We will retrain the model using images from these environments so that it learns about them to overcome this challenge. Further, we endeavour to incorporate feedback from the users.

We plan to use the trained models for concrete applications in Sub-Sahara Africa. One application will be based on the plantvillage dataset and enable small farmers to easily detect sicknesses on their plants and suggest countermeasures. The second application will allow authorities and non-governmental organisations to use satellite images to evaluate actual land use and possibly illegal activities. We will further assess their performance and applicability to developing countries and their user interaction.

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