Proceedings of the 2023 International Conference on Machine Learning and Automation
DOI: 10.54254/2755-2721/40/20230635

The application of automated machine learning in Malaria classification

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Abstract. As the majority of image classification tasks currently rely on intricate algorithms, crafting specific algorithms for image classification can be a complex and daunting endeavor. In this project, a method for the classification of malaria infected cells using automated machine learning technique is proposed, with the aim of using the Edge Impulse platform to demonstrate that automated machine learning can be used to achieve image classification. More specifically, the project uses the Edge Impulse platform and uses two different modules, Image with Transfer Learning and Image with Classification, and comparing the results of data. The test results were used to analyse the feasibility of the method. In short, the data set is trained and tested using two modules in the Edge Impulse platform, and if both modules achieve a satisfactory accuracy, it demonstrates the feasibility of automated machine learning techniques to image classification. Finally, through the test, the test results demonstrated that the two modules can reach almost 92% of the good accuracy, indicating that automated machine learning technology can be used to replace the algorithms to achieve image classification.

Keywords: Algorithms, Edge Impulse, Automated Machine Learning, Accuracy.

1. Introduction

Malaria is a disease transmitted by mosquitoes and is caused by Plasmodium parasites, it continues to be a global health issue, particularly in tropical and subtropical areas. The disease exacts a considerable annual toll in terms of human lives lost. Its complicated transmission cycle, wide range of symptoms, and risk of serious consequences highlight the significance of efficient prevention, diagnosis, and treatment measures. In the early field of cells recognition, the previous method of identifying malaria requires generating blood smears and examining these smears under a microscope to detect the Plasmodium genus, relying significantly on the expertise of skilled professionals [1]. However, this conventional method has low efficiency and need high level of expertise.

In contemporary times, algorithms have emerged as a catalytic impetus across a spectrum of industries, fundamentally influencing decision-making processes, catalysing transformative shifts in occupational methodologies, and optimizing procedural workflows. These advanced mathematical frameworks have enabled remarkable advances in automation, prediction, and customization. Algorithms are now a pervasive presence, altering and reinventing processes at every level, from banking to healthcare, retail to manufacturing. For instance, algorithmic trading strategies estimate risk in fractions of a second and then consider if execute transactions in finance. Light Gradient Boosting Machine (LightGBM) algorithm is demonstrated to be an efficient tool to predict financing risk in [2]. In manufacturing, algorithms play a vital role in improving numerous processes and activities in the manufacturing industry, the robot's path planning employs a genetic algorithm, while the fusion of virtual and tangible data substantially reduces the deviation in the movement path of tangible robots. This strategy contributes to the attainment of heightened precision in the movements of the robots [3], resulting in enhanced efficiency, lower costs, higher product quality, and less machine broken.

Especially in healthcare, algorithms aid in diagnosing diseases with disease diagnosis, medical imaging analysis, predictive analytics, and personalized treatment plans [4-6]. For example, attaining meaningful quantification of the average severity of Parkinson's disease symptoms with clinical significance [7], it allows healthcare practitioners to personalize medicines to the requirements of individual patients, resulting in improved outcomes. Also, Using Fuzzy Logic (FL), the test results are 15.4% more accurate than expert test results [8], the reason is algorithms more comprehensively evaluate patient data to provide higher diagnostic accuracy based on characteristics such as genetics, medical history, and therapy reactions.

In the previous time, malaria has been widely investigated, in [1], a shallow machine learning algorithm is provided to counter traditional methods, which have some obstacles in terms of sensitivity and specificity. However, due to the lack of clarity of the picture, shallow machine learning algorithm cannot complete the recognition task with high precision after all. In this past several years, the Convolutional Neural Network (CNN) stands as a highly favoured deep learning method within the realm of computer vision technology. According to [9], the authors gave a model with a deep CNN, which can obtain a high accuracy. This study aims to eliminate human interaction in selecting the proper algorithm, automate it, and target users who are unfamiliar with machine learning so that they may simply implement machine learning approaches.

In this regard, there are two kinds of models designed by using Edge Impulse. Each model made a classification on the cells to determine whether the input cells were infected with malaria. To compare the capabilities of different models in this dataset, this study used the Image with Transfer Learning and Image with Classifier for comparison. Finally, the machine automatically learns to recognize between different cells, and the two different automated machine learning models proposed, Image with Transfer and Image with Classifier, separately achieved Learning 91.53% accuracy in testing, achieved 92.14% accuracy. These results demonstrated it is feasible to use automated machine learning to classify whether cells are infected with malaria and giving two effective models.

2. Method

2.1. Dataset preparation

In the project, the dataset was collected from Kaggle [10], which is a prevailing platform for data science and machine learning competitions. The original dataset consisted of 27,558 data sets, with 13,779 parasitized and 13,779 uninfected but not fixed size, therefore, samples are subsequently to 96 × 96 for reducing training time, and each sample occupies approximately 11kb.

Initially, the dataset was uploaded, followed by an observed change in its quantity. As a result, it becomes necessary to address the dataset imbalance proactively. If not addressed, this imbalance could permeate into the training data, leading to a bias in the prediction model towards the more dominant class. Finally, there are 27, 538 samples in total, each dataset has 13, 769 samples, and then the samples are partitioned into a training set and a test set with a proportion of 2:8, which means there are 22, 028 in training set and 5, 510 in test set shown in Figure 1. After that, setting the colour mode of the dataset into the Red, Green, Blue (RGB).

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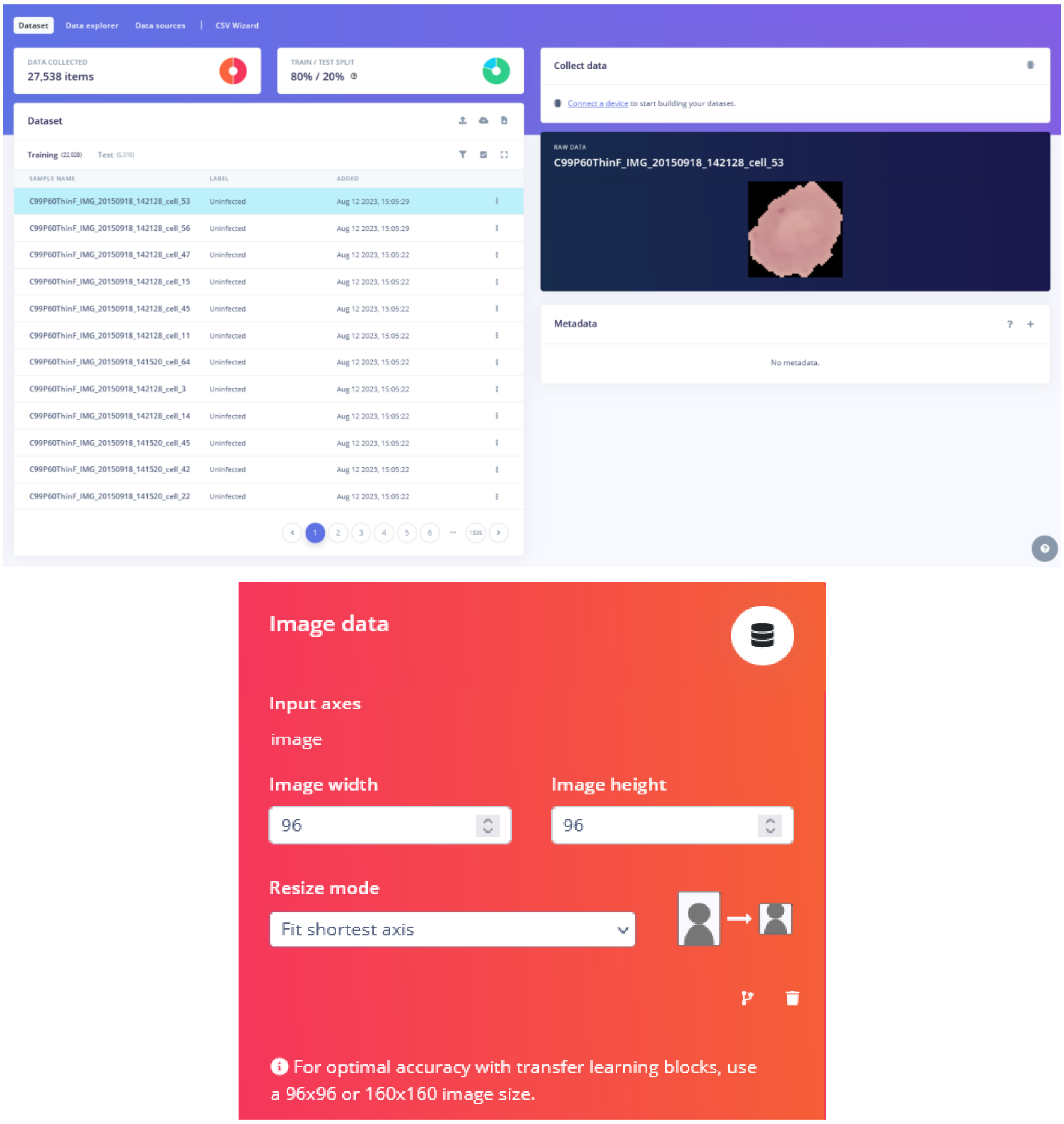

Figure 1. The details of splitting the uploaded data set into test sets and training sets.

2.2. Edge Impulse-based recognition

In this project, the platform Edge Impulse was first considered. Edge Impulse serves as an integrated development platform that empowers developers to craft, train, and deploy machine learning models tailored for edge devices. This platform facilitates the creation of intelligent applications capable of processing data within devices like sensors, microcontrollers, and other edge hardware. With an intuitive interface and a collection of pre-built machine learning components, Edge Impulse enables the seamless creation of personalized models. This expedites the development process and simplifies the direct deployment of machine learning solutions onto edge devices. Ultimately, Edge Impulse bridges the gap between proficiency in machine learning and the development of embedded systems, enabling the effortless implementation of intelligent edge applications. Also, the Edge Impulse platform supports CNN. CNN is a type of deep learning architecture commonly used for tasks involving image and visual data analysis. As the quantity of biological images rises, the effective classification of these images presents a formidable challenge, CNN hold potential in addressing this issue, offering a promising solution [11]. They are particularly effective in tasks like categorizing

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images, identifying objects, and segmenting images. CNN has changed the field of computer vision by allowing machines to comprehend and manage visual data such as photos and videos with unprecedented precision. The CNN represents a segment of the deep learning architecture intentionally crafted to emulate the human visual system's capacity to identify patterns, forms, and attributes within images. At the core of CNN lies their hierarchical composition of interconnected layers, each assigned the task of progressively extracting elevated-level characteristics from raw pixel data. The cornerstone module within CNN is the convolutional layer, which utilizes convolutional filters to meticulously scan the input image, capturing nuanced features including edges, textures, and configurations. Subsequently, the module's output undergoes pooling layers for data down sampling while retaining critical information. With network depth, fully connected layers integrate these attributes for the purpose of making classifications or predictions.

In this project, "Image" was chosen as a processing block since its job is to preprocess and normalize picture data, as well as to potentially reduce colour depth. About the learning block, the Classification and Transfer Learning are used. Classification is good at learning data patterns and can apply them to fresh data, it is an excellent for classifying movement or identifying audio, and Transfer Leaning is effective for fine-tuning a pre-trained image classification model on data, and it performs well even with small picture datasets. After using RGB to generate features, a graph demonstrated in Figure 2.

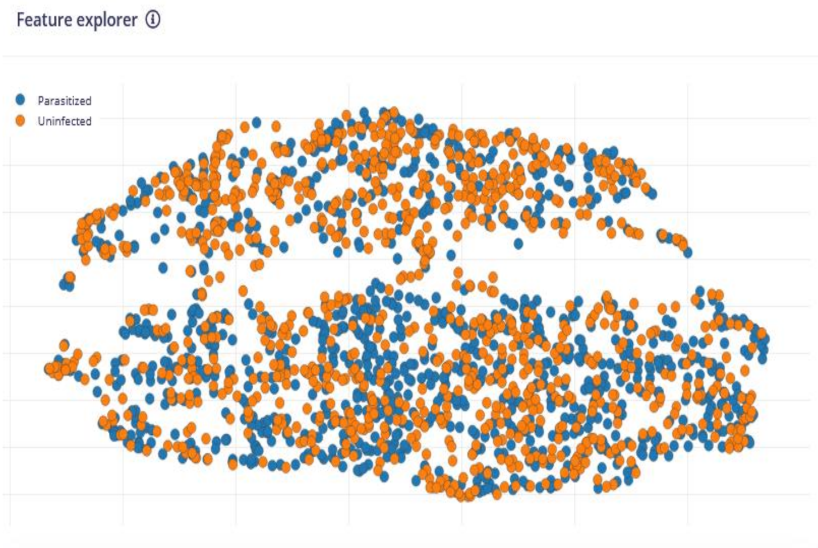

Figure 2. The visualization of generating features.

About Classification block, there exists a singular input layer and a sole output layer. and there are three different pool layers with the same 3 kernel size, and 1 Flatten layer. The whole architecture is shown in Figure 3. Number of training cycles are set to 3 to reduce the training time and learning rate is set to 0.0005 to ensures that the optimization process converges more slowly but steadily.

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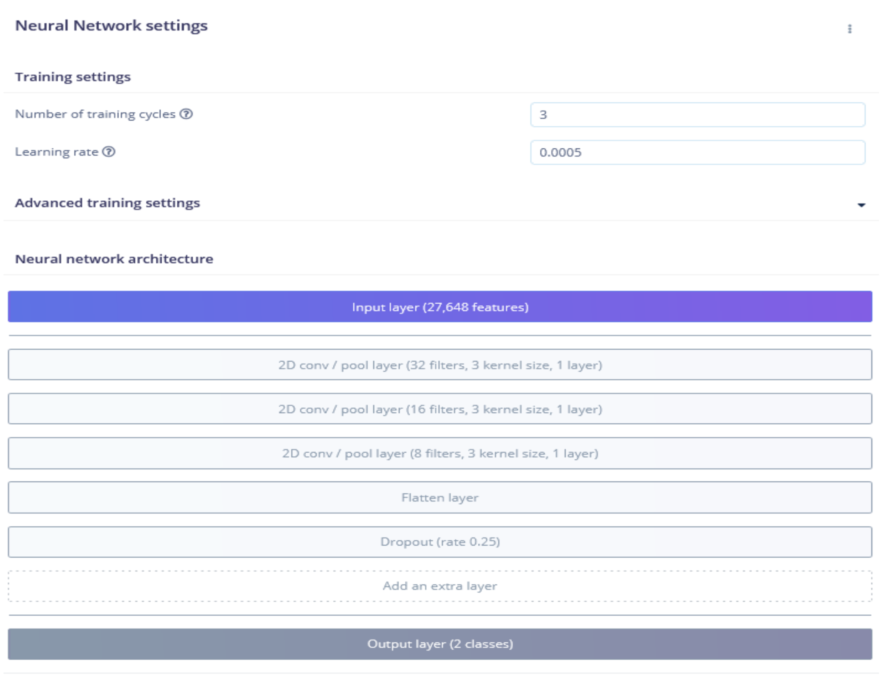

Figure 3. Neural Network settings and Neural network architecture-1.

In Transfer Learning block, the architecture is MobileNetV2 96x96 0.35 (final layer: 16 neurons, 0.1 dropout) shown in Figure 4, and its settings are same with Classification block.

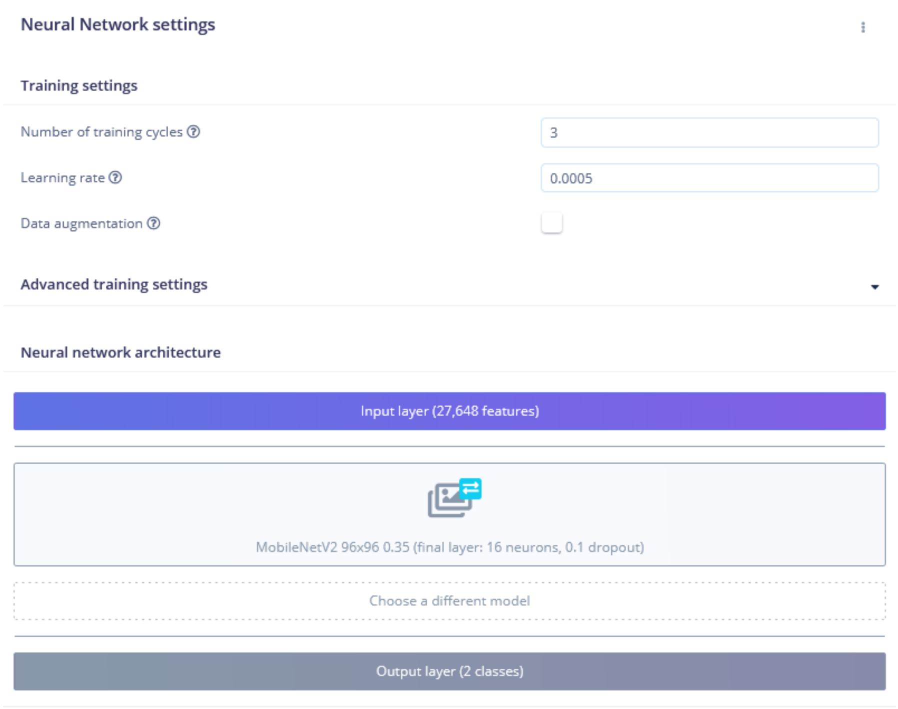

Figure 4. Neural Network settings and Neural network architecture-2.

3. Results and discussion

Through the manipulation of settings, equal training time for both types of models was achieved. Subsequently, two models were constructed. The selection of the superior model can be informed by referencing metrics such as training accuracy, Inferencing time, Peak RAM Usage, and Flash Usage. These specific data are illustrated in Table 1. The Table 1 illustrates the accuracy of the training of the two models is almost the same near 93.8%. They have a big gap, however, in the following data, the Inferencing time and Peak RAM usage of the model using Classification block cost much higher than the model using Transfer Learning block, which indicates that Image with Transfer Learning is more efficient when making real-time inferences more efficient at memory management and may perform better in resource-constrained environments. By contrast, the Flash usage of the model using Transfer Learning cost much more than the model with Image block. Finally, the model with Classification block is light higher than the model with Transfer Learning block, which are 92.14% and 91.53%. Although the difference is small, in some applications, slightly higher model test results can make a substantial difference, supporting better decisions.

Table 1. The training and testing results, and Inferencing, Peak RAM Usage and Flash Usage about two modules.

Processing Block	Learning Block	*Training Accuracy p*	Inferencing Time	*Peak RAM Usage*	Flash Usage	*Model Test Result*
Image	Transfer Learning	93.8%	389ms	0.593	947.8K	91.53%
Image	Classification	93.7%	7615ms	0.796	1.4M	92.14%

To sum up, although the Training Accuracy of Image with Classification and Image with Transfer Learning are similar, Image with Transfer Learning has obvious advantages in terms of Inference Time, Peak RAM Usage. Especially in applications that require real-time performance and lower resource overhead, it may be a better fit. However, to pursue higher Model test accuracy, the better model is using Image with Classification.

4. Conclusion

This study suggests the application of automated machine learning methods in the medical domain, particularly for tasks such as malaria-infected cell classification. The feasibility of this endeavor has been effectively demonstrated using the Edge Impulse platform. By leveraging a substantial dataset and employing two distinct modules, we assessed the effectiveness of our proposed methodology. The experimental results highlight the promising prospects of this approach, with both modules consistently achieving an accuracy rate of nearly 92% under constant parameters. It can significantly contribute to early diagnosis and intervention. Looking ahead, plans involve trying and testing diverse modules, enabling the identification of the most optimal one for cells classification. This effective approach, driven by the pursuit of enhanced accuracy and versatility, holds the promise of contributing significantly to medical research and diagnostic practices, ultimately aiding in the improvement of healthcare outcomes.

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