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Improving Soybean Disease Prediction by Performing Late-Stage Re-Training Using Fireworks Algorithm

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Introduction

Food resources are a necessity, but access is tainted by **crop ailments**, resulting in a steady decline in the worldwide production of crops. Therefore, detecting diseases and preventing their spread from curbing losing crops is essential. To do so, ML algorithms have come into play to detect and distinguish diseased crops from healthy ones.

A drawback is that observing morphological traits alone is not always accurate; early detection to curb diseases in different crops is being investigated currently.

Objectives

Direction One

First training the model normally with one optimizer

Direction Two

Retraining the model using another optimization algorithm

Design and Contribution

ML algorithms such as ANNs will be used for this study.

The 'Soyabean Disease' Dataset, accessible in the UCI Machine Learning Repository, is used in the study.

The idea of late-stage training came from the need to create more accurate models using an amalgamation of current technologies to create a way to train a model that is better than the individual sum of its parts.

During the first round of training, impacting accuracy and loss metrics might be more convenient than closing that last 10% gap. This is where the finding of the present study comes in.

When deciding what algorithm to choose for the optimization step during the training of neural network models, there is also a need to take **time** into consideration.

However, it can be intuitively understood that different training sections benefit most from different optimization techniques.

Late-Stage Re-Training

In orthodox ML processes, we have specific sets of optimizers that we use to train our models. We provide a new methodology to use various optimizers at different steps of training to get even better results than using a single optimizer, allowing us to extract better results from our model.

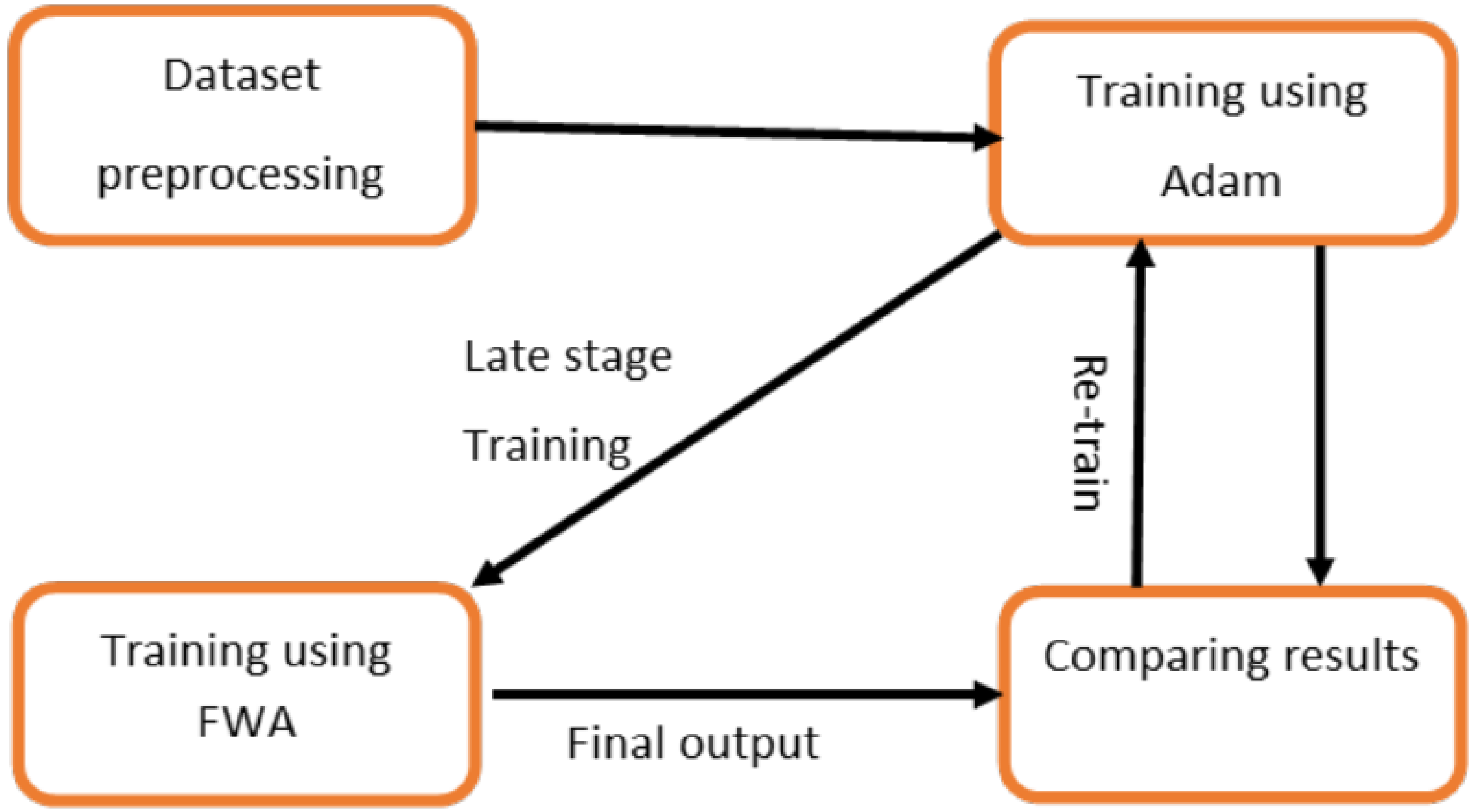
The proposal: a novel method of training and optimizing a model to get as optimal a result as possible.

Aim: to shed light on alternative ways of using multiple optimizers with different properties to get better results, achieving an incremental increase in accuracy.

This is done by switching the optimizer after training once, performing **Late-Stage Re-Training (LSRT).**

In the present study, we test our hypothesis through the use of 2 different optimizers, **Adam** and **Fireworks** for their unique properties, better results are obtained.

Adam is used first for most of the training process and is later switched out to *Fireworks* for re-training this model.



Flow diagram for the proposed study

Adam Optimizer

An optimization technique for gradient descent.

Useful when working with large problems involving a lot of data or parameters.

It requires less memory and is efficient.

It is useful and implemented in the research due to its quick convergence and momentum.

Fireworks Algorithm

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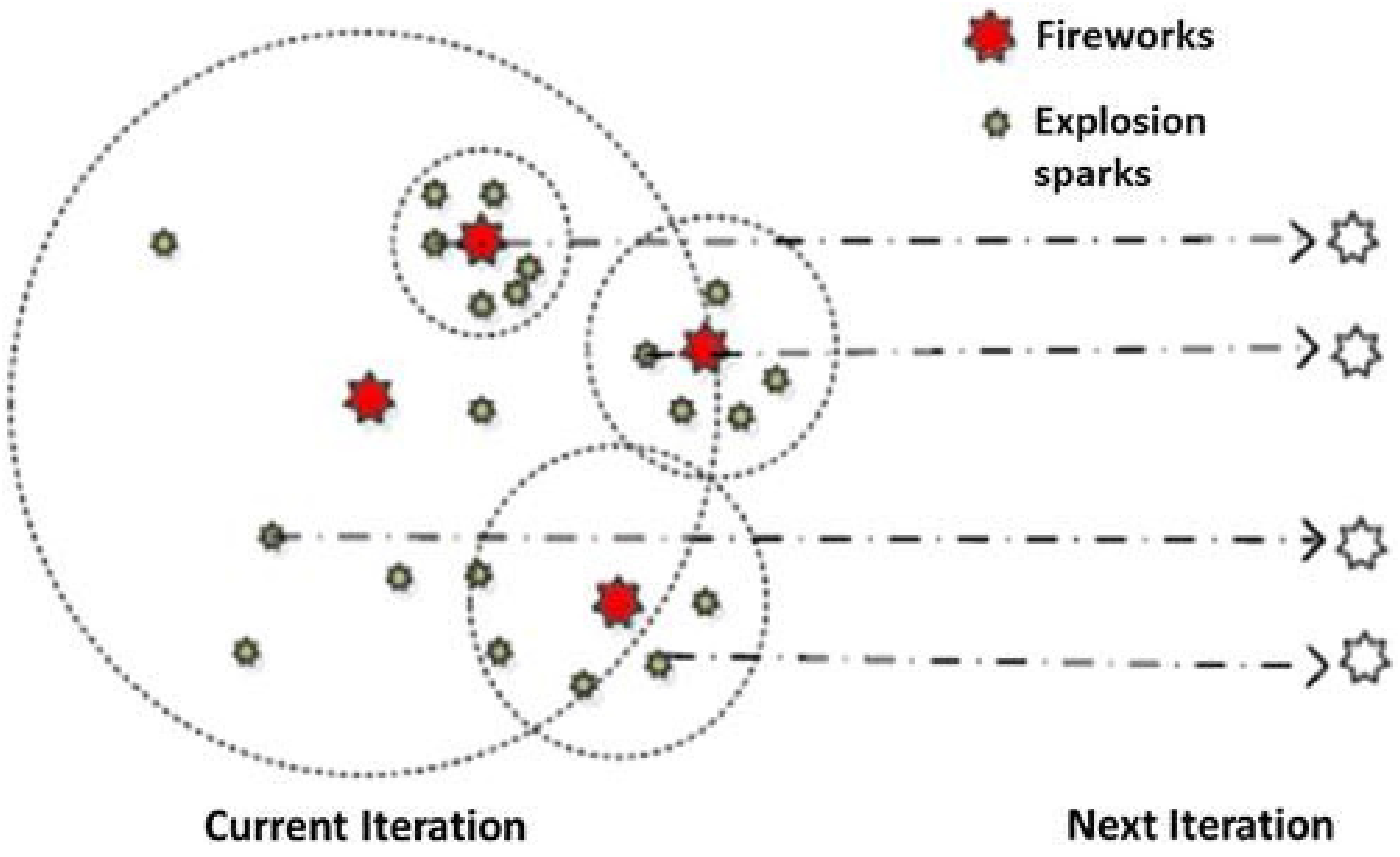
A novel swarm intelligence algorithm, called **Fireworks Algorithm (FA):** proposed for global optimization of complex functions.

Explores a very large solution space by choosing a set of random points confined by some distance metric.

Expectation: one or more of the randomly selected points would produce interesting results, allowing for a more focused search.



Described in terms of the working of fireworks: Moving into a suitable position, they explode into radiant lights of various shapes, which is dependent upon the fireworks’ design.

Each firework has specific characteristics and is defined by a unique explosion and the various positions at which they explode.

The algorithm evaluates each spark and terminates if an optimal location has been found, otherwise repeats with another set of locations.

It has been attracting more and more research interest and has been widely employed in many real-world problems due to its unique search manner and high efficiency.

Why use both?

It is a great method to get out of any local minima that the study might have gotten trapped into due to the linear descending structure of Adam.

When fireworks itself is used as the only optimizer used during training, it does not give appropriate results, nearing only a measly 60% train accuracy on average and therefore being much behind industry-standard results that are generated from legacy algorithms. On further inspection, however, the present study finds that after the initial burst, the rate of increase of the 'train' accuracy decreases exponentially. This makes Fireworks a great secondary algorithm, while it performs poorly as a primary optimization algorithm.

A **drawback** of the Adam optimizer: in some scenarios, Adam does not converge to the optimal solution. Other major issues with FWA: low convergence and low accuracy.

If used in tandem, the operations rectify each other's drawbacks: training using Adam provides a quick, accurate starting point. Later passes using FWA takes care of local minimums, and brings the solution to the global minimum.

Other issues: Weight Decay problem in Adam and Explosion Tuning in Fireworks, can be circumvented using alternative versions of these algorithms (dynFWA) and AdamW or AMSGrad.

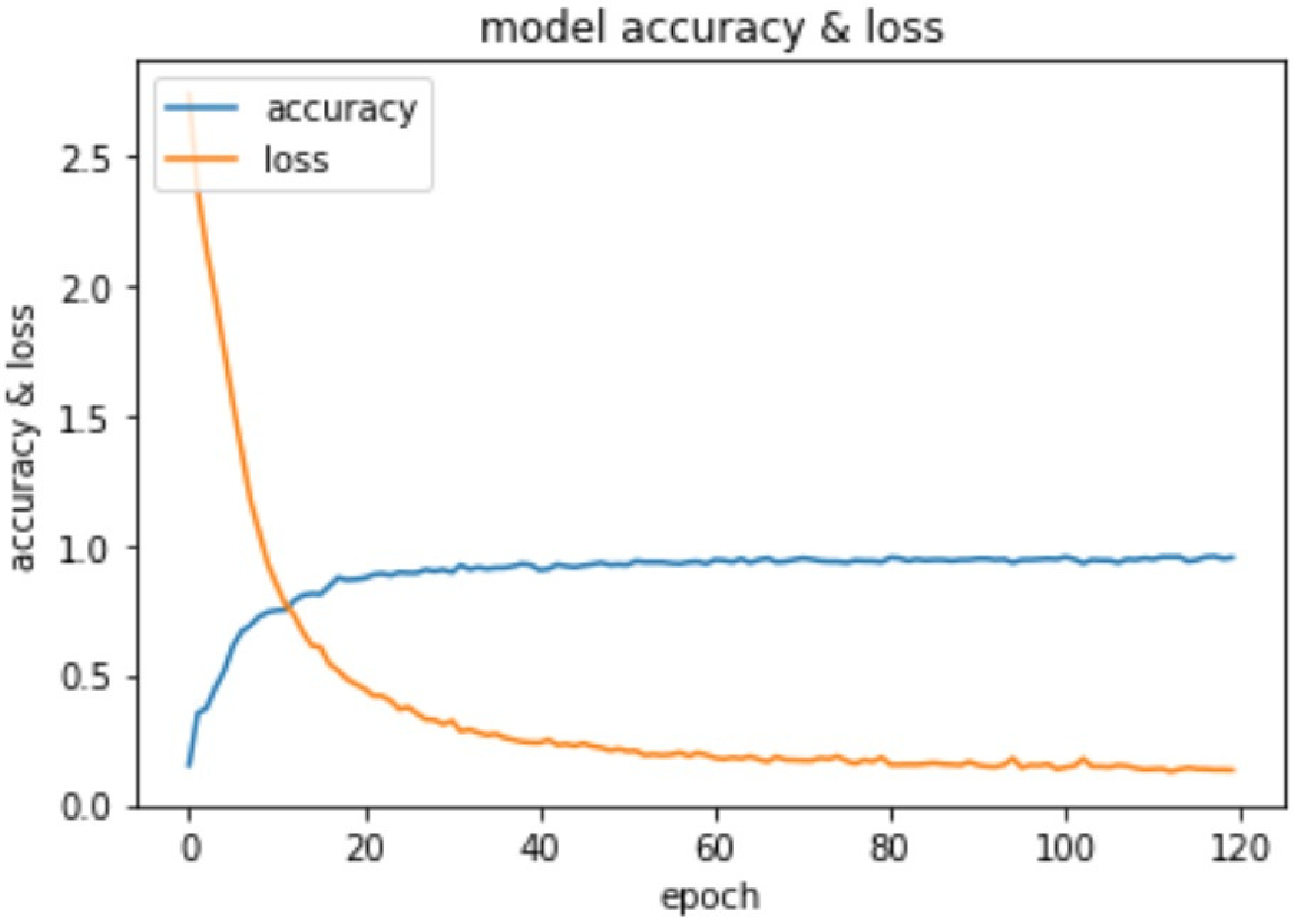
The pair of optimizers used in the present study might not be the best in terms of all-rounded use with other dataset as well. This makes the process of choosing the appropriate pair of optimizers more difficult.

Results and Discussion

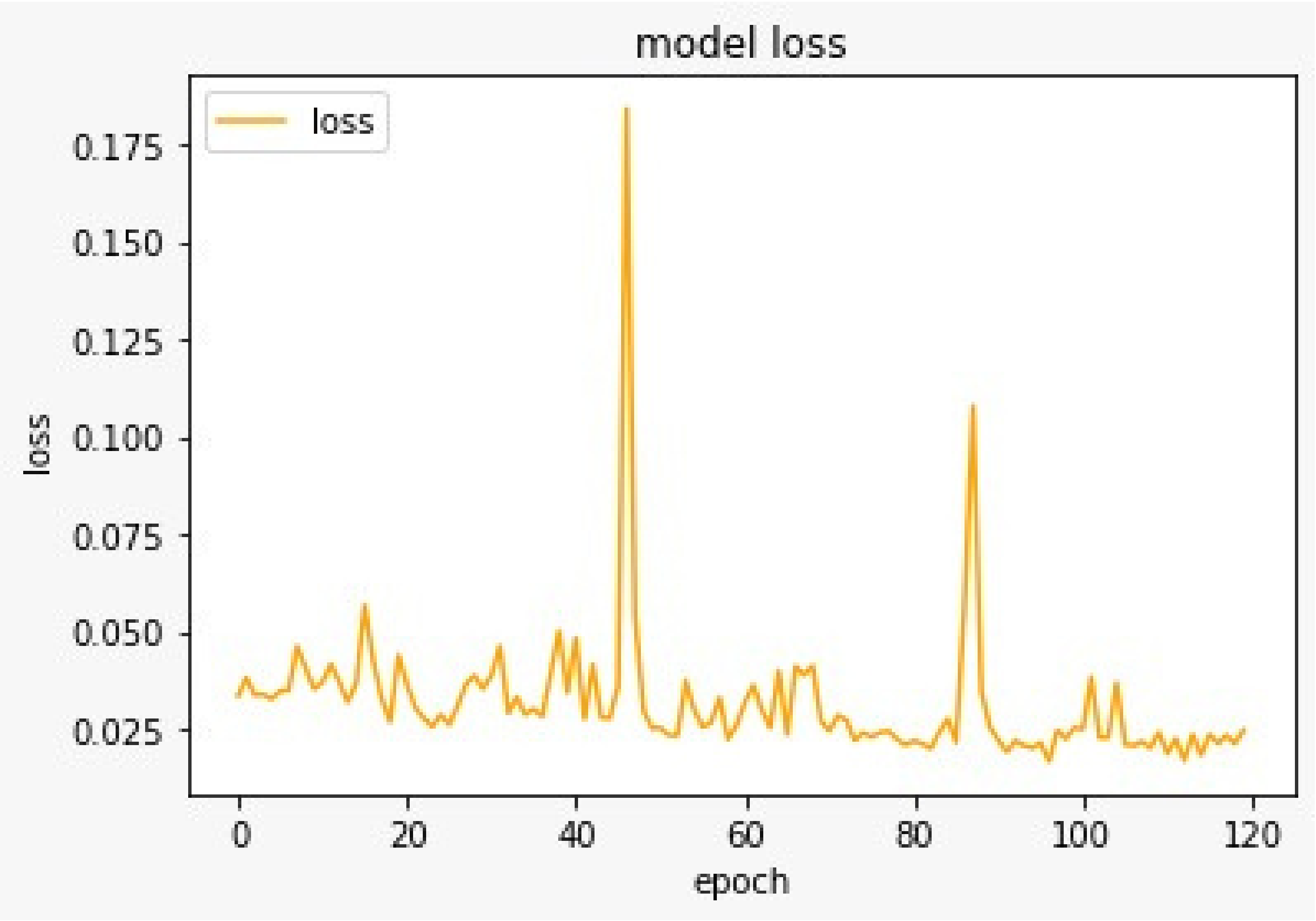
The usage of LSRT is comparable to machine learning models such as Linear Discriminant Analysis (LDA), Random Forest (RF) and Support Vector Machine (SVM).

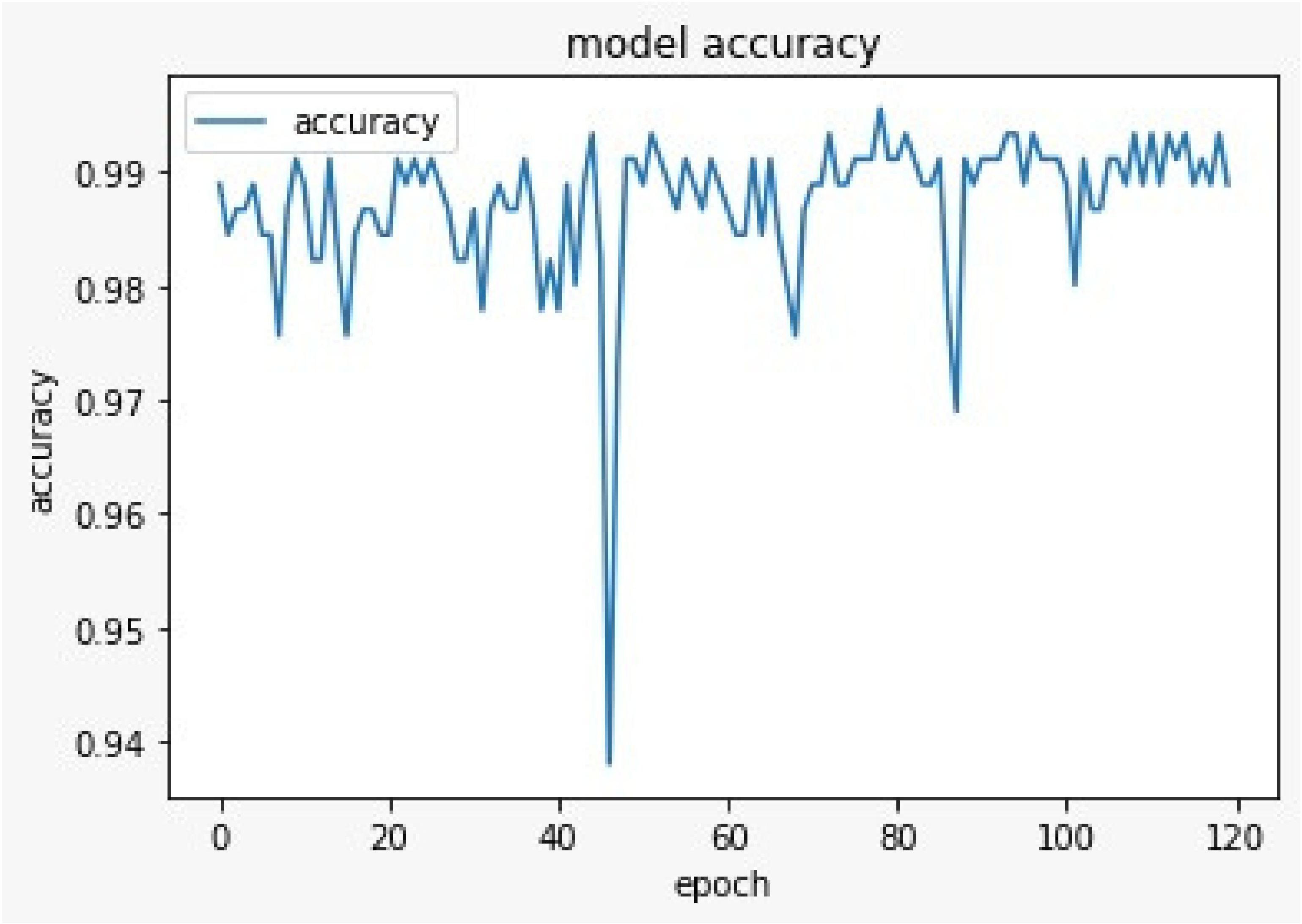
Hence, using the Fireworks Algorithm and LSRT, the present study was able to create a model that was **4%** more accurate on train data and nearly **2%** on test data.

First Pass (Using Adam) and Results

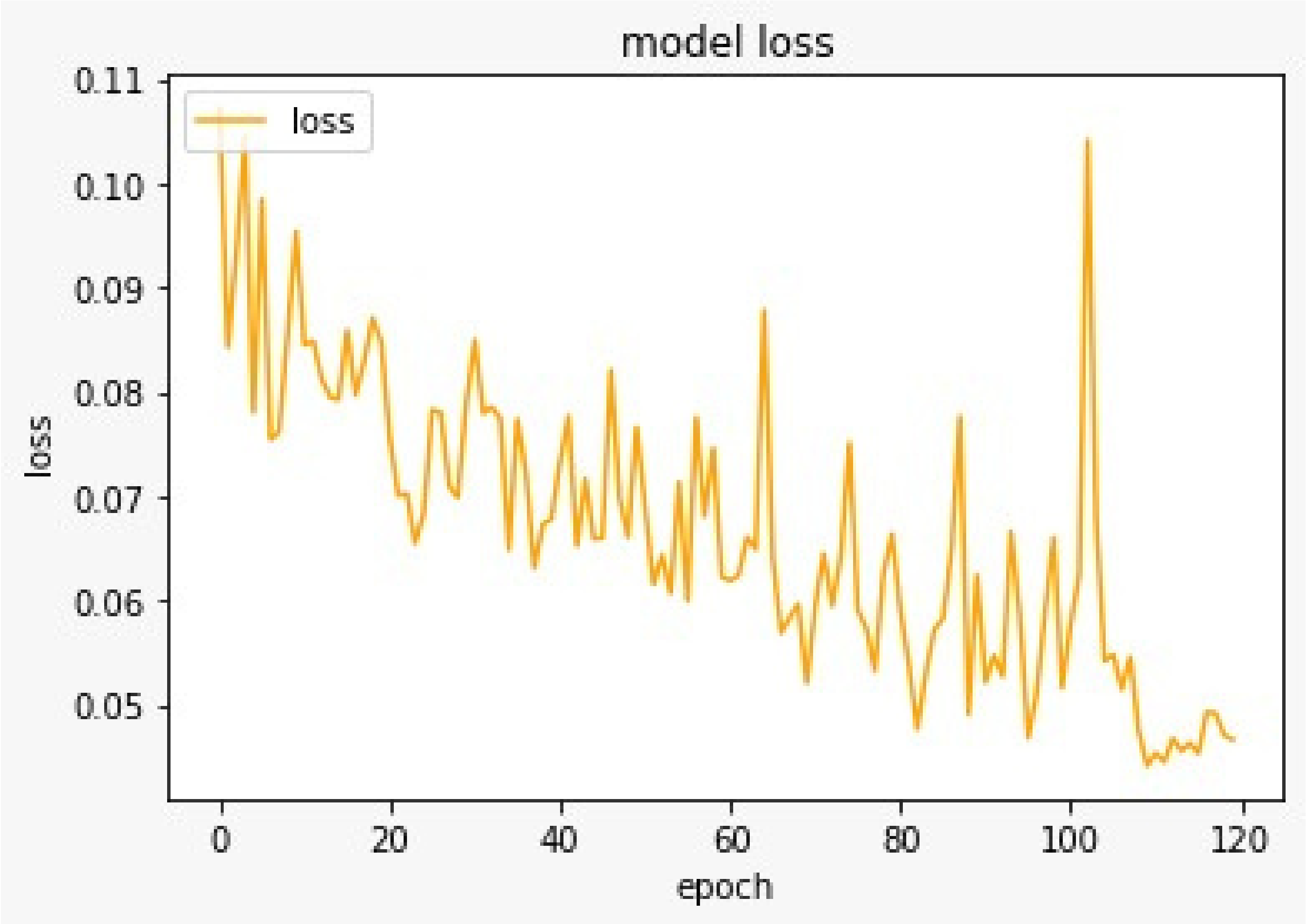


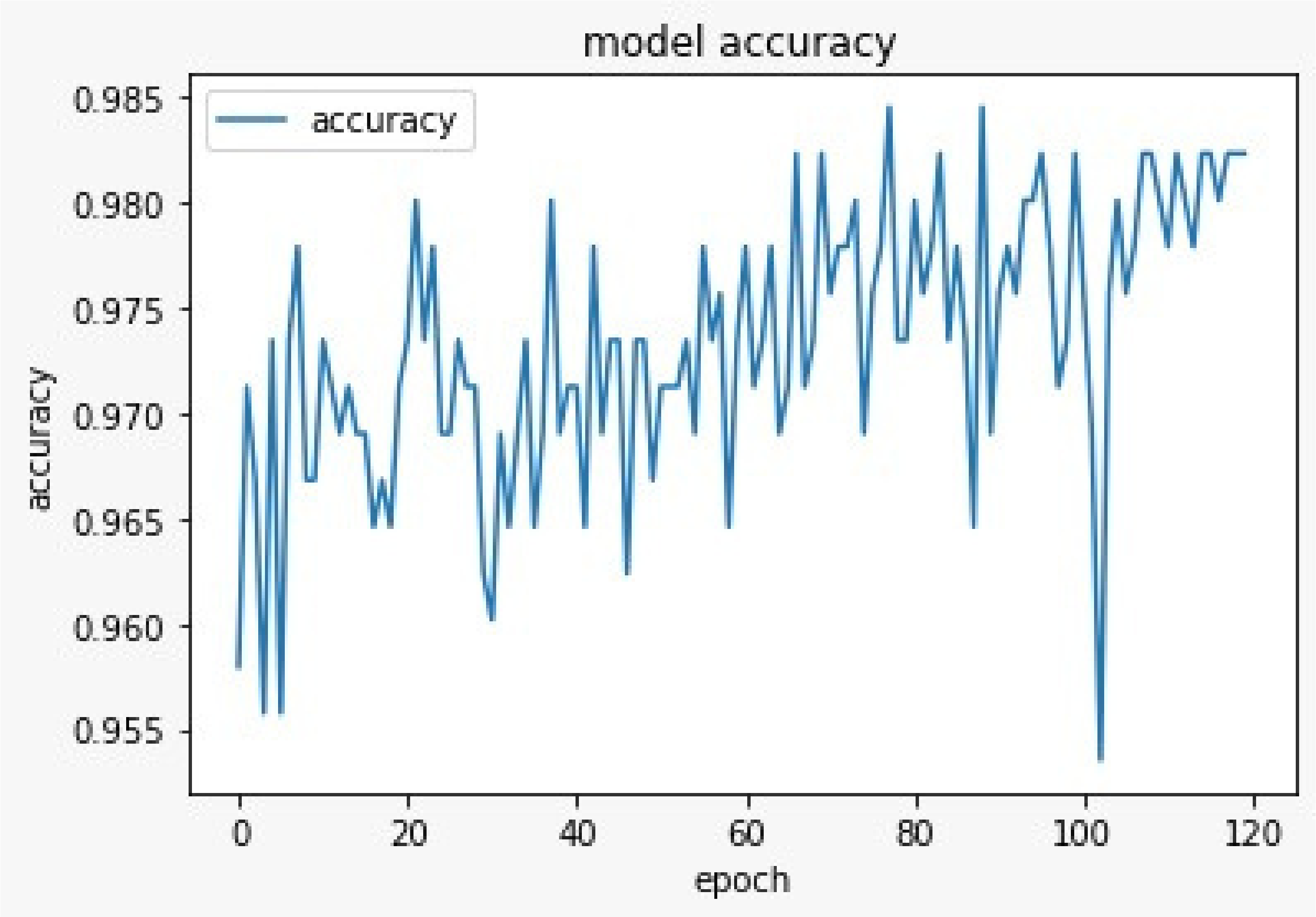
Second Pass (Using Adam) and Results





Third Pass (Using FWA) and Results





THE OUTPUT OF 3 - STAGE TRAINING

Operation	Training Accuracy	Testing Accuracy
First Pass(Adam)	94.47%	90.58%
Second Pass(Adam)	97.12%	89.69%
Third Pass(FWA)	98.89%	92.03%

This methodology is tested on the Soybean dataset. The above process leads to an average of 2-3% increase, thus obtaining a training accuracy of 98.9%.

Conculsion

A new way of getting better results was discovered on both our test and train data with the help of the **hybrid implementation of optimizers.** The training accuracy increases after initially plateauing while using the original optimizer, and the test accuracy increases by a massive margin after initially retraining with the Adam optimizer. Compared to the research conducted by other parties on classification tasks (such as soybean diseases), the work done by the present study provides results that make retraining lucrative for better results.

Using the FA and LSRT, the present study was to create a model that was **4% more accurate** on train data and **nearly 2% on test data**.

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