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Convolutional Neural Network Based Nutrient Deficiency Classification in Leaves of *Elaeis guineensis* Jacq.

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***Abstract*: Nutrient deficiency is one of the main causes of the decline in oil palm production. In fact, oil palm farmers cannot diagnose the symptoms of the nutrient deficiency by themselves. Generally, the collected leaf samples need to be analyzed using laboratory equipment which consumes time and budget. In this research, the leaf samples including fronds 17 and 25 were collected from 37 oil palm trees. Frond 17 was used to analyze the amounts of Nitrogen (N), Phosphorus (P), Potassium (K), Magnesium (Mg), and Boron (B). Based on biochemical tests on palm leaves collected, the relationship between oil palm leaf characteristics and its amounts of nutrients was studied. Deep learning models were developed using Convolutional Neural Networks (CNN) to diagnose nutrient deficiency in oil palm from the leaves' images. The nutrient results were classified into 3 groups: deficiency, normal, and excess. Totally, 682 images from frond 25 from trees across a farm were used for image data collection. Various CNN benchmark architectures were used to analyze the performance of nutrient deficiency classification but the separable convolutional CSBio2020 and BettaNet architectures were found to be ideal enough for the set of data collected. Separate models were trained to predict the levels of each nutrient. The models' average accuracy is 77.2% for CSBio2020 and 80.4% for BettaNet. The average precision, recall, and F1 score are 0.75, 0.75, and 0.747, respectively, for CSBio2020 and 0.76, 0.813, and 0.775, respectively, for BettaNet. Many studies in the area dealt with few nutrients but this paper has all the nutrients analyzed and a deep learning architecture with parameters optimized to fit all in one with more optimal performance when compared to other existing methodologies.**

Keywords: Oil palm, Nutrient deficiency, Convolutional Neural Networks (CNN), CSBio2020**,** BettaNet

I. Introduction

Oil palm (*Elaeis guineensis* Jacq.) is the main source of vegetable oil used worldwide for domestic, commercial food, and cosmetic industries. Oil palm is a monocotyledon in the family Arecaceae. It has pinnately compound leaves consisting of 2 parts, rachis with 250-300 leaflets attached on it and petioles that attached to the trunk. Its fruit is drupe composed of pericarp and seed. Pericarp can be separated into 3 layers orderly from outside, exocarp, mesocarp, and endocarp. The two latter layers are used to produce palm oil and palm kernel oil respectively.

Nutrients play an important role in the growth of oil palm. Lack of nutrients can affect oil palm growth and reduce oil palm product yield. When some nutrients are deficient, oil palms usually show characteristics on their leaves. Deficiencies in the five main nutrients of oil palm; nitrogen (N), phosphorus (P), potassium (K), magnesium (Mg), and boron (B), which are focused on in this paper show characteristics on leaves summarized in *Table 1.*

References	Nutrient deficiency	Characteristics
[1][2][3]	Nitrogen	pale green, yellow color leaf
	Potassium	yellow, orange spot on leaf
	Magnesium	bright orange color leaf
	Boron	wrinkled, hooked leaf
[2][3]	Phosphorus	short, narrow, and conical shape trunk, dark green leaf

Table 1. Characteristics of oil palm's Nitrogen, Phosphorus, Potassium, Magnesium, and Boron deficiency.

Deep learning algorithms using convolutional neural networks can identify nutrient diseases in plants with high accuracy. For studies on oil palm, researchers use several techniques to classify oil palm's nutrient deficiencies based on leaves images such as using near-infrared reflectance spectroscopy to classify oil palm's nutrient diseases. Support Vector Machine (SVM) technique, Artificial neural network, and fuzzy interference system were also utilized. A brief review of the approaches is presented in *Table 2*.

References	Method	Crops	Deficiency	Accuracy (%)
[4]	Artificial neural network	Oil palm	N, K, Mg	86.11
[5]	Support vector machine	Oil palm	N, P, Mg	95.00

[6]	Fuzzy inference system	Oil palm	N, K, Mg	82.67
[7]	Convolutional neural network (VGG)	25 plant species	58 distinct classes of [plant, disease]	99.53
[8]	near-infrared reflectance spectroscopy	Oil palm	N, P, K	NA
[9]	Deep network with auto encoders	Maize	N, P, K	100
[10]	Convolutional neural network	14 crop species	26 diseases	99.35
[11]	Convolutional neural network	Tomato	N, K, Ca	87.27
[12]	Convolutional neural network	Okra	NA	86.00

Table 2. Overview of machine learning techniques for nutrients disease classification.

There are many other deep learning methodologies proposed for animals [27] and insects [28] as well. The conventional way of nutrient analysis in oil palm is done by analyzing the leaves. Leaves samples are normally collected from frond 17. The number order of oil palm fronds can be counted from the first fully opened frond at the center of the tree as frond 1. Number order of fronds located in a straight line under frond 1 is added by 8 per layer as shown in Figure 1. Collected leaf samples were analyzed by 2 techniques, inductively coupled plasma atomic emission spectroscopy (ICP-OES) [13] and the Kjeldahl method [14]. The principle of ICP-OES is to quantify each element in a sample using the wavelengths emitted by the heated atoms to the excited state. This technique can be used to determine the amount of P, K, Mg, and B. The second technique, the Kjeldahl method, was used to measure nitrogen content. It consists of 3 main steps, digestion, distillation, and titration. These techniques have to be done in the laboratory, which is expensive and time-consuming for oil palm farmers. Therefore, this paper uses deep learning to identify five nutritional deficiencies (N, P, K, Mg, and B) from oil palm leaf images by implementing the proposed architecture. Frond number 17 is a standard level for oil palm nutrient analysis. Samples collected from this method is subjected to analysis using Kjeldahl method. Frond number 25 is a standard level which normally exhibits nutrient deficiency which can be identified by observation by experts and experienced farmers. So, the samples from this frond are used to classify using deep learning.

Figure 1. Number of oil palm fronds, as marked in the photo are frond 1, 9, 17, and 25.

Convolutional Neural Networks are a type of artificial neural networks with fixed or customized set of hidden layers mostly used for problems associated with Computer Vision. There are many pretrained convolutional neural networks ranging from LeNet [18], the first ever CNN developed. Other architectures include AlexNet [19], Efficient Net, NasNet, DenseNet, MobileNet,VGG 16 and 19 etc. The architectures of CSBio 2020 [16] and BettaNet [17] are used in the experiments listed in this paper. The architectures of CSBio in Figure 2 and BettaNet given in Figure 3.

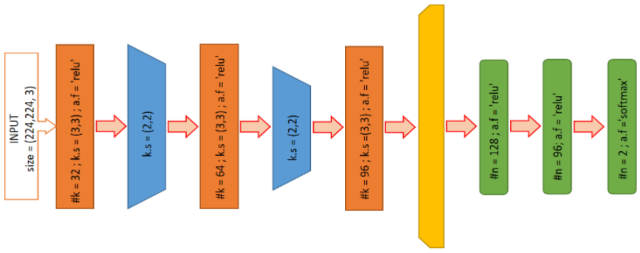

Figure 2. CSBio 2020 architecture

According to the CSBio 2020 architecture presented, Depthwise separable convolutional layers are given in orange, Maxpooling layers are given in blue, Flatten layer is given in yellow and dense layers for the fully connected neural network are given in green. This is a transformed version of VGG architecture used in [16] for performance evaluation. This architecture replaces the normal convolutional 2D layer to depthwise separable convolutional layers.

Figure 3. BettaNet architecture

BettaNet architecture is a modified version of ResNet 50. The experimentations in this paper involved BettaNet with ResNet 50 but the convolutional 2D layers totally rewired as per BettaNet. The remaining part of the paper is organized as follows: Methodology for experimentation is described in section II, Results in section III, Discussion in section IV and concluded in section V.

II. Methodology

A. Data collection

1) Leaf Sample Collection

All leaf samples in this research were collected from the Suksomboon palm oil industry, Chonburi, Thailand. Firstly, leaflets from fronds 25 were collected from distinct 37 oil palm trees for image acquisition. Then, from the tree of which frond 25's leaflets were collected, approximately 20 leaflets from frond 17 were collected for the nutrient content analysis. According to international standards, leaflets from frond 17 were used for nutrient content analysis. For image acquisition, frond 25 is chosen for the reason that its leaflets apparently show more characteristics of nutrient deficiencies than frond 17's.

2) Image Acquisition

The leaflets from frond 25 had been placed on white background and images were taken by a digital camera (Panasonic, Lumix). In total, 682 photos were taken. Some examples of collected photos are shown in **Figure 4**. The images are captured using a controlled environment with a constant lighting exposure on all the samples collected. For any dataset, change in lighting impacts the accuracy though there are methodologies dealing with lighting invariant methodologies. The methodologies reported had not reported a significant change when tested with a random initial experimentation.

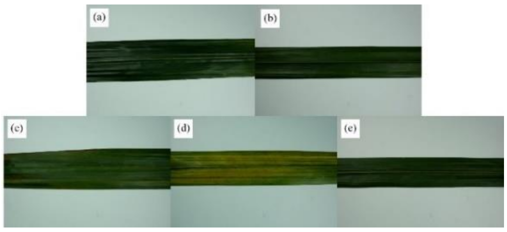

Figure 4. Examples of collected images of deficiency leaves, (a) B deficiency, (b) K deficiency, (c) Mg deficiency, (d) N deficiency, and (e) P deficiency.

3) Nutrient Analysis

The collected leaves samples from frond 17 had been cleaned, ground, filtered to get fine powders, and kept in desiccator. The samples were then used to analyze the amount of P, K, Mg, and B using ICP-OES, and to analyze the amount of N using Kjeldahl method. 0.2500±0.0002 grams of sample were weighed for ICP-OES technique and 0.1000±0.0002 grams were used for Kjeldahl method.

B. Program Development

Convolutional neural network architectures were used in deep learning-based classification. During the image selection step, the nutrient deficiency oil palm leaf without fungal, bacterial, or other disease characteristics were used to avoid distractions. The images of the different levels of each nutrient, N, P, K, Mg, and B, were divided into 3 groups. The deficient, optimum, and excess nutrients were classified based on the reference values shown in *Table 3*.

Five models of each architecture were constructed to predict the level of N, P, K, Mg, and B. Architectures of CSBio2020 [16] and BettaNet [17] were utilized. The program was written in Python using TensorFlow and Keras.

Oil palm's age	Nutrient	Deficient	Optimum	Excess
Less than 6 years	Nitrogen (wt%)	< 2.50	2.60-2.90	> 3.10
	Phosphorus (wt%)	< 0.15	0.16-0.19	> 0.25
	Potassium (wt%)	< 1.00	1.10-1.30	> 1.80
	Magnesium (wt%)	< 0.20	0.30-0.45	> 0.70
	Boron (mg/kg)	< 8	15-25	> 40
6 years or more	Nitrogen (wt%)	< 2.30	2.40-2.80	> 3.00
	Phosphorus (wt%)	< 0.14	0.15-0.18	> 0.25
	Potassium (wt%)	< 0.75	0.90-1.20	> 1.60
	Magnesium (wt%)	< 0.20	0.25-0.35	> 0.60
	Boron (mg/kg)	< 8	15-25	> 40

Table 3. Macronutrient analysis values of oil palm leaves at the deficient, optimum, and excess level of nutrients [15]

Then, the images were resized to 224x224 and rescaled by dividing by 255. After that, they were split into training and testing sets by using 90%-10% rule. For the training set, data augmentation was done by shearing, zooming, and flipping. The model was trained with the preprocessed training set of 100 and 200 epochs for CSBio2020 and 500 epochs for BettaNet. Testing set was used to evaluate the model to calculate Accuracy, Cross-entropy loss, Precision, Recall and F1 score of the models.

III. Results

The results of the experiment were divided into two parts: nutrient content with quantitative analysis and performance evaluation of deep learning architectures.

A. Nutrient content analysis

The amounts of nutrients were classified into 3 groups of nutrients: deficient, optimum, and excess nutrients by referring to *Table 3*. From the 37 oil palm samples, 17, 0, 13, 3 and 3 trees were deficient in N, P, K, Mg, and B, respectively. 19, 9, 17, 17, and 11 trees contain optimum amounts of N, P, K, Mg, and B, respectively. And 1, 28, 7, 17, and 23 trees contained excess amounts of N, P, K, Mg, and B, respectively, as shown in *Table 4*.

Nutrient	Number of trees		
	Deficient	**Optimum**	**Excess**
N	17	19	1
P	0	9	28
K	13	17	7
Mg	3	17	17
B	3	11	23

Table 4. The number of oil palm trees with deficient, optimum, and excess content levels of N, P, K, Mg, and B.

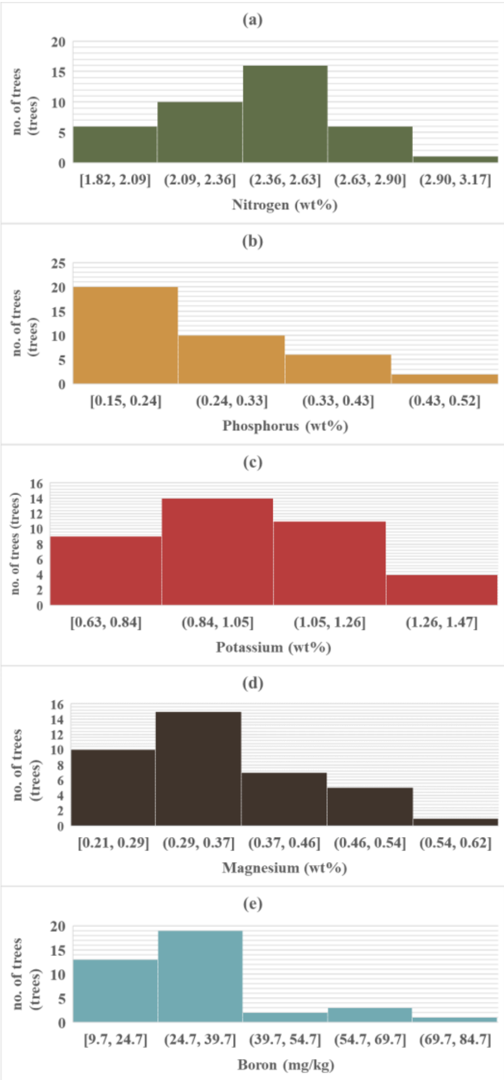

Figure 5. Histograms showing distribution in nutrient amounts contained in collected samples, (a)-(e) are N, P, K, Mg, and B, respectively.

From the results of nutrient analysis, histograms for the distribution of nutrient content are shown in **Figure 5**. Histograms of N and K are similar to normal distribution while those of P, B, and Mg are more right skewed.

Correlation analysis between various nutrient content results in *Table 5*. It can be seen that P and K had negative correlation with each other while other pairs of nutrients showed positive correlation.

	N	**P**	**K**	**Mg**	**B**
N	1	0.079784	0.112664	0.058397	0.295396
P		1	-0.15459	0.091907	0.375829
K			1	0.066243	0.033622
Mg				1	0.31316
B					1

Table 5. Correlation coefficient Analysis among N, P, K, Mg, and B

The statistical results of nutrient analysis are shown in *table 6*. Amounts of N ranged between 1.82-2.99 wt% and the mean was at 2.38wt%. Amounts of P ranged between 0.15-0.49 wt% and the mean was at 0.25 wt%. Amounts of K ranged between 0.63-1.35 wt% and the mean was at 0.10 wt%. Amounts of Mg ranged between 0.57-0.21 wt% and the mean was at 0.35 wt%. Amounts of B ranged between 9.73-72.56 mg/kg and the mean was at 30.34 mg/kg. Values of S.D. and variances of the 5 nutrients can be ranked from high to low as B, N, K, P, and Mg respectively.

B. Performance Evaluation of CNN

Table 7 presents previous architectures' testing accuracies, including LeNet, AlexNet, VGG 16, VGG 19, Efficient Net, and ResNet at 100 and 200 epochs. With 200 epochs, Lenet had the lowest testing accuracy of 23.33% and Efficient Net B7 had the highest testing accuracy of 69.77%. However, these architectures still had significantly lower testing accuracy than CSBio2020 and BettaNet which are shown in *Table 8* and *9*. All these experiments were conducted using the setup recommended by [26]. NVIDIA RTX 2060 8GB GPU with 16 GB RAM were used with Intel Core i5 processor. The experiments carried out in Table 7 and 8 is supported with a validation accuracy a factor of 5-fold cross validation by which the dataset is randomly labelled with sample number and divided into five blocks. Each block is tested against the training of remaining blocks. The testing performance obtained is taken a mean of all the folds in the cross validation and reported from Table 7 onwards.

Statistical values	N (wt%)	P (wt%)	K (wt%)	Mg (wt%)	B (mg/kg)
Mean	2.38	0.25	0.99	0.35	30.34
Median	2.45	0.24	0.96	0.35	26.40
S.D.	0.26	0.09	0.20	0.08	14.09
Variance	0.07	0.01	0.04	0.001	198.38
Maximum	2.99	0.49	1.35	0.57	72.56
Minimum	1.82	0.15	0.63	0.21	9.73

Table 6. Statistical values from nutrient analysis results: mean, median, S.D., variance, maximum and minimum.

C.

S.No	Architecture (Reference)	Testing Accuracy with 100 epochs of training (%)	Testing Accuracy with 200 epochs of training (%)
1	LeNet [18]	26	23
2	AlexNet [19]	37	33
3	VGG 16 [20]	40	45
4	VGG 19 [21]	39	41
5	VGG 19 with separable convolution [21]	56	65
6	Efficient Net B7 [22]	69	70
7	ResNet 152 [23]	45	49

Table 7. Preliminary testing of CNN architectures reporting average accuracy

As shown in *Table 8*, *Table 9*, and **Figure 4** through **6**, the training accuracy of CSBio2020 at 100 and 200 epochs ranged from 95.28-98.21% and 99.19-99.67%, respectively. BettaNet at 500 epochs had training accuracy ranging from 90.76-100%. CSBio2020 had lower training accuracy than the training accuracy of BettaNet at 500 epochs for P, K, and B. However, CSBio2020 at 200 epochs had slightly better performance than BettaNet for N. Both CSBio2020 at 100 and 200 epochs also had higher accuracy than BettaNet for Mg. Cross-entropy loss values of CSBio2020 at 100 and 200 epochs, and BettaNet at 500 epochs ranged between 0.05-0.11, 0.006-0.028, and 0.001-0.229, respectively. CSBio2020 had averagely higher cross-entropy loss values than BettaNet, except for Mg which of BettaNet was significantly the highest.

The testing accuracy of CSBio2020 at 100 and 200 epochs, and BettaNet at 500 epochs were in the range of 64-88%, 70-85%, and 71-85%, respectively. For testing accuracy, BettaNet had better performance than CSBio2020 in all nutrients except P. It can also be seen from CSBio2020 that training accuracies of all 5 models increased significantly from 100 to 200 epochs while testing accuracies of all models except P model increased slightly. The CSBio 2020 architecture was set up with a default learning rate, batch size of 50 and Leaky Relu was used. In the actual version of CSBio 2020 normal Relu was used. In the initial experimentation Leaky Relu activation was found to be better than Relu in this dataset.

Architecture	Separable Convolution CSBio2020									
Nutrient	N		P		K		Mg		B	
Epochs	100	200	100	200	100	200	100	200	100	200
Training accuracy (%)	97.88	99.67	97.4	99.51	95.28	99.19	96.76	99.35	98.21	99.35
Cross-entropy loss	0.0514	0.0063	0.052	0.0078	0.1122	0.0283	0.0831	0.0221	0.0671	0.0232
Testing accuracy (%)	74	75	88	84	64	72	69	70	68	85

Table 8. Training accuracy, cross-entropy loss, and testing accuracy of accuracy of CSBio2020 at 100 and 200 epochs

In BettaNet architecture, the 50-layer version was used instead of the 152 layered original version. Batch size was defined as 50 to get uniform configuration as CSBio. The original version's batch size was 25. Learning rate was set to default and Relu was used as the activation function.

Architecture	**BettaNet (500 epochs)**				
Nutrient	**N**	**P**	**K**	**Mg**	**B**
Training accuracy (%)	98.86	99.67	99.51	90.76	100

Cross-entropy loss	0.034	0.0137	0.0054	0.2288	0.000721
Testing accuracy (%)	83	79	85	71	84

Table 9. Training accuracy, cross-entropy loss, and testing accuracy of BettaNet at 500 epochs

(a) Nitrogen		Actual class		
		Deficient	Excess	Normal
Predicted class	Deficient	19	0	10
	Excess	0	2	1
	Normal	5	1	30

(a) Nitrogen		Actual class		
		Deficient	Excess	Normal
Predicted class	Deficient	19	0	10
	Excess	0	2	1
	Normal	5	1	30

(b) Phosphorus		Actual class		
		Deficient	Excess	Normal
Predicted class	Deficient	-	-	-
	Excess	-	43	7
	Normal	-	4	13

(c) Potassium		Actual class		
		Deficient	Excess	Normal
Predicted class	Deficient	19	1	4
	Excess	2	6	4
	Normal	2	6	23

(d) Magnesium		Actual class		
		Deficient	Excess	Normal
Predicted class	Deficient	4	1	0
	Excess	0	22	8
	Normal	0	11	19

(e) Boron		Actual class		
		Deficient	Excess	Normal
Predicted class	Deficient	6	0	1
	Excess	1	39	2
	Normal	3	3	13

Figure 9. Confusion matrices of CSBio2020, (a) N model, (b) P model, (c) K model, (d) Mg model, and (e) B model.

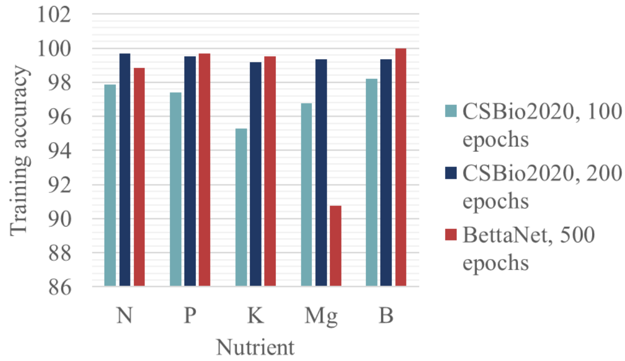

Figure 6. Training accuracy of models CSBio2020 at 100 and 200 epochs and BettaNet at 500 epochs

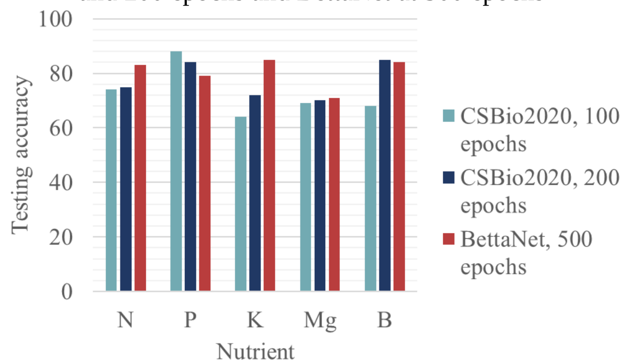

Figure 7. Cross-entropy loss of models CSBio2020 at 100 and 200 epochs and BettaNet at 500 epochs

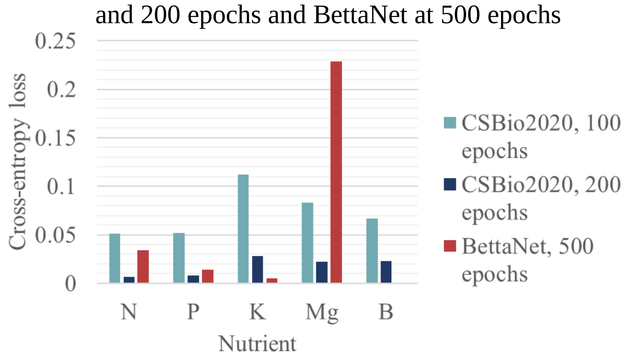

Figure 8. Testing accuracy of models CSBio2020 at 100 and 200 epochs and BettaNet at 500 epochs

Confusion matrices of CSBio2020 are shown in **Figures 9.** From the confusion matrices, precision, recall and F1 score of CSBio2020 and BettaNet can be calculated by these formulas [24].

$$\text{Precision} = \frac{TP}{TP+FP} \quad (1)$$

$$\text{Recall} = \frac{TP}{TP+FN} \quad (2)$$

$$\text{F1 score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (3)$$

From the calculations, precision, recall, and F1 score of CSBio2020 are demonstrated in *Table 10* through *12*. The average precision values of N, P, K, Mg, and B models were 0.73, 0.78, 0.68, 0.78 and 0.78, respectively. The average recall values of N, P, K, Mg, and B models were 0.72, 0.81, 0.67, 0.72 and 0.82, respectively. The average F1 score of N, P, K, Mg, and B models were 0.72, 0.80, 0.67, 0.75 and 0.79 respectively. The data are shown in *Tables 11* through *13*.

It can be seen that prediction for excess K was the least accurate among other nutrients, noted by the smallest precision, recall, and F1 score which made the overall average F1 score of K model become the smallest, consequently. The P model with only 2 predictable classes showed the greatest average F1 score. N, Mg, and B models had the best performance for optimum, deficient, and excess classes, respectively noted by the highest F1 scores in each class.

	N	P	K	Mg	B
Deficient	0.79	-	0.83	1	0.6
Optimum	0.73	0.65	0.74	0.7	0.81
Excess	0.67	0.91	0.46	0.65	0.93
Average	0.73	0.78	0.676667	0.783333	0.78

Table 10. CSBio2020 precision in each class for 5 nutrients

	N	P	K	Mg	B
Deficient	0.66	-	0.79	0.8	0.86
Optimum	0.83	0.76	0.74	0.63	0.68
Excess	0.67	0.86	0.50	0.73	0.93
Average	0.72	0.81	0.68	0.72	0.82

Table 11. CSBio2020 recall in each class for 5 nutrients

	N	P	K	Mg	B
Deficient	0.72	-	0.81	0.89	0.7
Optimum	0.78	0.7	0.74	0.67	0.74
Excess	0.67	0.89	0.48	0.69	0.93
Average	0.723333	0.795	0.676667	0.75	0.79

Table 12. CSBio2020 F1 score in each class for 5 nutrients

As shown in *Table 13* through *15*, BettaNet's precision values for N, P, K, Mg, and B models were 0.73, 0.81, 0.79, 0.66, and 0.81, respectively. The average recall values of N, P, K, Mg, and B models were 0.78, 0.88, 0.8, 0.79, and 0.81 respectively. The average F1 score of N, P, K, Mg, and B models were 0.75, 0.825, 0.80, 0.70, and 0.81 respectively. P, with only 2 classes, has the highest average precision, recall, and F1 score, followed by B, K, and N, while Mg is the lowest in all three values.

	N	P	K	Mg	B
Deficient	0.80	-	0.80	0.50	0.75
Optimum	0.75	0.98	0.77	0.72	0.86
Excess	0.65	0.64	0.79	0.77	0.81
Average	0.73	0.81	0.78	0.66	0.81

Table 13. BettaNet precision in each class for 5 nutrients

	N	P	K	Mg	B
Deficient	0.75	-	0.83	1.00	0.86
Optimum	0.83	0.82	0.83	0.70	0.90
Excess	0.78	0.94	0.74	0.67	0.68
Average	0.78	0.88	0.8	0.79	0.81

Table 14. BettaNet recall in each class for 5 nutrients

Table 15. BettaNet F1 score in each class for 5 nutrients

	N	P	K	Mg	B
Deficient	0.80	-	0.82	0.67	0.80
Optimum	0.75	0.89	0.80	0.71	0.88
Excess	0.70	0.76	0.77	0.71	0.74
Average	0.75	0.82	0.79	0.69	0.80

Table 15. BettaNet F1 score in each class for 5 nutrients

IV. Discussion

From the results of nutrient analysis, oil palm trees lacking P were not found. Among collected samples, there are only trees with optimum and excess P. Therefore, it is not possible to create a complete dataset for P. The correlation analysis showed that the correlation coefficient between P and K was negative. This means that these two elements have an inverse relationship. While the correlation coefficients between other pairs of elements are positive, meaning that there is a direct relationship between them. According to the Confusion matrices, it was found that the models were not able to distinguish leaves with optimum and excess nutrients from each other very well. However, the study has not yet found any data to determine the physical differences between palm leaves with optimum and excess nutrients. The effects of over-nutrient in oil palm have not been studied, but in other plants, studies have shown that excess nutrients are toxic to plants and decrease yields [25]. From the results, the final testing accuracies from the proposed neural network architectures including CSBio2020 and BettaNet were between 70-85% which is remarkably higher than the pre-existing architectures. So far no transfer learning is used in the case of CSBio and BettaNet as the dataset is unique and cannot be normalized with the performance reported by transfer learning. These accuracies are expected to be increased by expanding the data size, collecting samples from multiple areas, and experimenting with more architectures in order to extend the program into a real practical application. The scope of this application leads to creation of mobile application using Tensorflow.js, IoT based application deployed in NVIDIA Jetson Nano and integration of deep learning-based computing in Platform for AI available in Alibaba Cloud.

V. Conclusion

The data including images and analysis of the nutrient content of oil palms were collected to construct a dataset. Deep learning models with convolutional neural networks were used to classify the images into 3 groups: deficient, optimum, and excess nutrients. The capabilities of all 5 models for each architecture were measured from testing accuracy, precision, recall and F1 score, with all 5 models having an average testing accuracy of 77.2% for CSBio2020 and 80.4% for BettaNet. The average precision, recall, and F1 score are 0.75, 0.75, and 0.747, respectively, for CSBio2020 and 0.76, 0.813, and 0.775, respectively, for BettaNet.

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