ICIC Express Letters
Volume **14**, Number **10**, October **2020**

ICIC International ©2020 ISSN 1881-803X
pp. 1025–1032

MOBILE IMAGE PROCESSING APPLICATION FOR CACAO'S FRUITS PEST AND DISEASE ATTACK USING DEEP LEARNING ALGORITHM

Basri[1,*], Rosmawati Tamin[2], Harli A. Karim[3], Indrabayu[4] and Intan Sari Areni[5]

[1]Informatics Study Program
[2]Information System Study Program
[3]Agrotechnology Study Program
Universitas Al Asyariah Mandar
Polewali Mandar, Sulawesi Barat 91315, Indonesia
*Corresponding author: basri@unasman.ac.id; { rosmawatitamin; harli }@unasman.ac.id

[4]Department of Informatics
[5]Department of Electrical Engineering
Universitas Hasanuddin
Jl. Perintis Kemerdekaan Km. 10, Makassar 90245, Sulawesi Selatan, Indonesia
{ indrabayu; intan }@unhas.ac.id

Received December 2019; accepted March 2020

Abstract. *This study aims to apply image processing techniques that can identify the initial symptoms of pests and diseases of cacao fruits based on mobile applications. The system applied the concept of expertise in the field of cacao cultivation with image processing techniques for pre-processing and the deep learning algorithm as a machine learning system for object pattern recognition. Image processing techniques are integrated into application software to be able to identify the pixel characteristics of the cacao fruit surface images in agricultural land in real time. The image of cacao was further classified into four types of classification in 615 datasets. The image dataset is processed by a deep learning system into vector values to be compared against new input data captured using a mobile camera. The results of this research showed that the accuracy of the system in recognizing cacao fruit objects reaches 100% in the identification of cacao fruits attacked by pests, diseases, and normal classification with an average similarity of objects to the database for images of normal condition by 83.75%, disease attack by 84.87%, and pests attack by 80.80%.*

Keywords: Image processing, Cacao fruit, Pest, Disease, Mobile application

1. **Introduction.** The implementation of early identification of cacao fruits that have been attacked by pests and diseases with mobile-based application has never been done before, although for image processing techniques to support cacao cultivation, has done a lot, like in determining the maturity of cacao [1], also for identifying the types of defects in cacao [2]. This study aims to apply image processing techniques with deep learning models combination on mobile applications to identify the initial symptoms of pests and diseases of cacao fruits.

Previous research to identify pests and diseases of cacao fruits was carried out by developing a pest attack identification system based on a Graphical User Interface (GUI) with less accuracy [3]. Efforts in gaining computational effectiveness previously were also carried out by analyzing binary threshold data and grayscale levels by applying the Gabor filter algorithm [4]. The results of these studies provided unsatisfactory results, so it needs a computational method that can provide a better level of accuracy with

DOI: 10.24507/icicel.14.10.1025

better computational complexity on mobile devices. Therefore, it must be following the compatibility of the mobile operating system [5].

The pattern recognition and feature extraction methods in mobile-based applications require techniques that can speed up the computing process [6]; besides the resulting accuracy must be maximum [7]. The challenge for developing mobile-based applications with image processing systems is the complexity of the system in processing extensive image data, although it does not affect the number of datasets [8], so the system is expected to extract the features from training data and be accurate in the learning process. For this reason, this study carried out the implementation of artificial intelligence with the concept of deep learning algorithm that was developed in a mobile application device.

Recent evaluation related to the deep learning algorithms implementation on mobile devices showed better results, where the deep learning model that was implemented can significantly improve accuracy compared with traditional neural network methods that were previously applied. Also, in terms of computational complexity, this method has been designed with better results, even on a standard mobile phone [9]. This method is developed from a standard neural network model but with the acceleration recognition model and locally applicable and faster on mobile devices [10].

Development of deep learning models is suitable for the mobile application framework as this study so that with this approach, farmers can use a mobile application as a mobile expert system that is faster, accurate, and can be used anytime at a cacao plantation location. Also, this study shows preliminary studies in the research roadmap to apply image processing in that field, especially in cacao cultivation, so that it becomes a preliminary study for mobile-based implementation research on identifying problems in crop cultivation. Sequentially after Section 1 explaining objectives of the study, then related works and state of the art are discussed in Section 2, the implementation of deep learning in several models developed is addressed in Section 3, and then an explanation regarding the implementation of mobile devices is presented in Section 4. Results and analysis are shown in Section 5, and finally, discussion is made in Section 6.

2. **Cacao's Fruit Pest and Disease Identification in Related Works.** The prototype of disease, pest, and normal cacao fruit features recognition was initially built using GUI-based programming applications with MATLAB programming and has passed the analysis stage to be implemented to the applied stage with mobile-based applications integration as the achievements of previous research [3,4]. The implementation of the Gabor filter algorithm in GUI applications built using MATLAB begins with the image recognition stage for the preprocessing system. This process is carried out to normalize the data used. Data taken from the camera in the form of RGB file types are transformed into grayscale and threshold binary for the next process of resizing by resizing the image to a size of 92×110 pixels so that the data can be filtered out by the Gabor filter evenly. Gabor filter is the initial method used because it is considered a maximum as a feature extraction method and pattern recognition [11]. Implementation of Gabor filter on GUI-based applications was not able to provide maximum results, and difficulties in implementation in mobile programming because each image database that was embedded must be loaded in the form of a bitmap image extracted into pixel values to be matched with new input data.

The stages of the study for implementation towards mobile applications are then carried out using the Local Binary Pattern (LBP) algorithm. LBP is widely implemented in real-time recognition and accelerates in feature extraction time [12]. The concept of LBP is labeled the pixels of an image by doing a 3×3 neighboring thresholding process of each pixel as the mean value and converts the result to a binary value. Next, LBP calculates the local texture representation by comparing each pixel with the surrounding pixel environment [13]. The initial implementation used a database using training data consisting of 20 data with identification of normal cacao fruit and 40 data, each with the identification of disease and pest-infested cacao.

Testing the results of the cacao fruit recognition in this study was carried out to measure its accuracy. Accuracy measurements are performed using the Receiver Operating Character (ROC) technique [14]. The use of ROC in determining the desired model parameters must follow the characteristics of the classifier model [15], so that this study only measures the performance of the recognition system that was built by measuring the level of Accuracy (ACC), as follows:

$$\text{Accuracy } (ACC) = \frac{\sum(TP) + \sum(TN)}{\sum(TP) + \sum(TN) + \sum(FP) + \sum(FN)} \quad (1)$$

If the system accurately detects the number of objects according to the actual situation, it is called True Positive (TP), but if the system detects the wrong object, then it is declared False Positive (FP). False Negative (FN) is a situation where the system does not detect the desired object, while True Negative (TN) is a value when the system does not detect unwanted objects.

3. **Deep Learning Implementation.** Deep learning is one area of machine learning that utilizes artificial neural networks to implement problems with large datasets [16]. The use of the cacao fruit image dataset as the case in this study is undoubtedly included in the classification of large datasets. By adding more layers, the learning model in deep learning techniques can better represent labeled image data. In addition to the concept of artificial neural networks, many layers of computing systems that are running can learn with speed, accuracy, and large scale [17]. Feature engineering is one of the main features of deep learning to extract useful patterns from data that will make it easier for models to distinguish classes. The algorithm used in feature engineering can find important general patterns to distinguish between classes in deep learning. Complex models will undoubtedly require a long training time so that the concept of deep learning using GPU is very commonly used [18].

The initial step of the deep learning implementation flow begins with the feature extraction Layer. The process that occurs in this section is "encoding" from an image into features in the form of numbers that represent the image (feature extraction). The feature extraction layer consists of two parts, namely visible layer and hidden layer. The case of the classification of cacao fruit is made into a convolutional layer, known as the visible layer. The result of the visible layer filter will be to shift the "dot" operation between the input and the value of the filter to produce an output or commonly referred to as an activation map or feature map of the hidden layer.

The next process occurs object classification using the visible layer filter. The dimensions of the input used initially are the 5×5 pixel data matrix, then convolution is performed with a 3×3 filter and a stride of 2, and then a feature map with a 2×2 size is obtained. However, if we add zero paddings by 1, the feature map will be 3×3 in size (more information will be generated). From these stages, the implementation of cacao's fruits image recognition with three types of classifications is illustrated in Figure 1.

4. **Mobile Application Design.** The deep learning method, like an object classification algorithm, is integrated into a mobile-based application system with Java programming. Like Figure 2, the system is built with a simple concept with four main menus (Home, Early Detection, Information, and About). Identification is made through the Early Detection menu, and then the application displays the captured image (b) and cropping (c) to display the results of the classification of the three conditions (d).

Figure 3 shows the process of identifying the characteristics of cacao fruits affected by the disease, pests, and the condition of cacao fruits categorized as normal fruit. The introduction process begins with real-time image capture in the cacao farm (a), and then

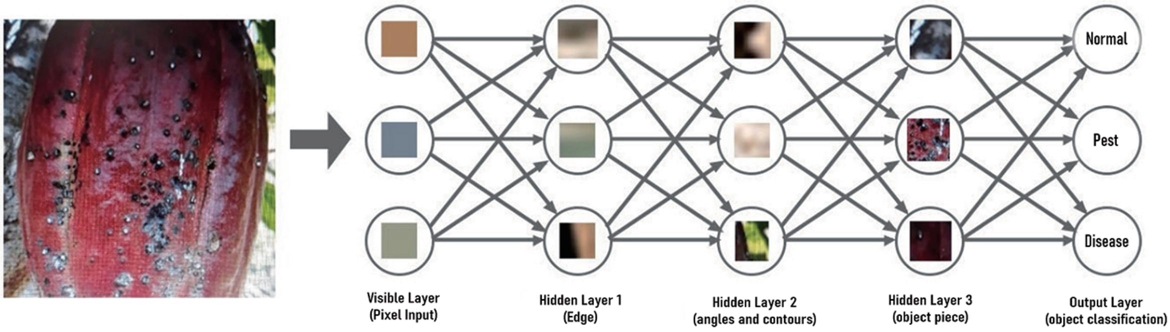


FIGURE 1. Deep learning concept for cacao's fruits classification condition

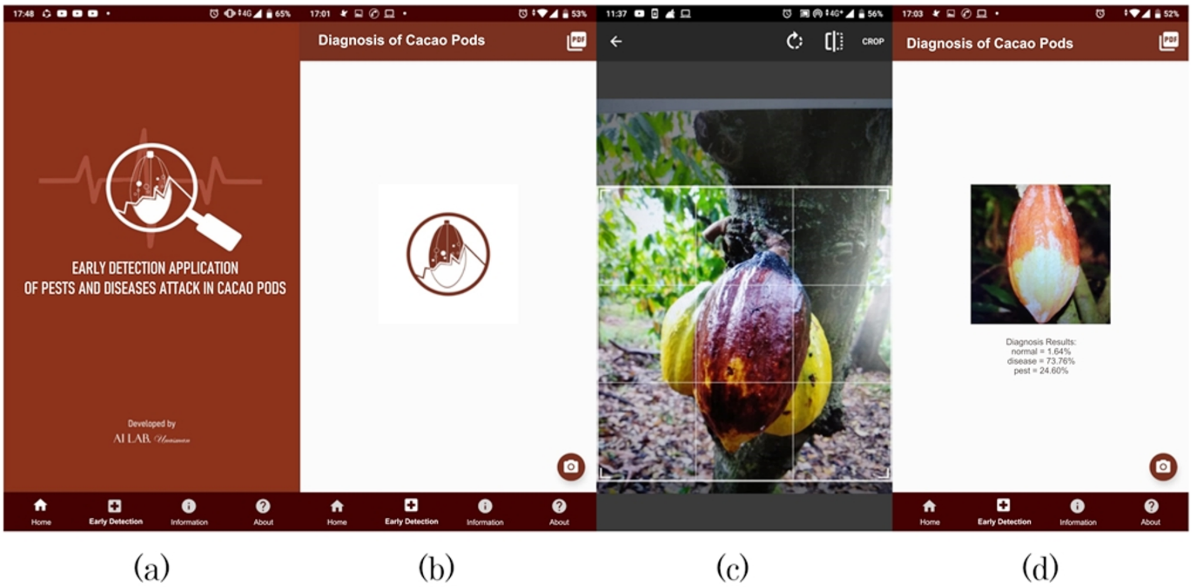


FIGURE 2. Flowchart and design interface application

615 cacao fruit image data was classified into a database with expert identification of 176 fruits, pest 208 images, and normal 231 images classification. The image processing system collected the data with a histogram system which is processed by the deep learning algorithm and then developed to perform feature extraction and feature learning to be further classified into three types of classification in the database. The effort to simplify the data training process is that databases are stored in vector form using GUI-based tensor flow libraries and embedded into mobile applications as shown in Figure 1 and explained in Section 3. In the next process, when capturing new image data, the system will process as the initial process, but with feature recognition that is matched to the database. The system built on the result of identification (d) displays the level of similarity in the three object classifications, and it is to show the suitability of the new object to the database.

5. **Results and Analysis.** The testing of new objects was carried out on a massive scale at a cacao plantation location involving 20 users with each mobile phone device that has been installed. Each user classifies three cacao in each type of classification so that each respondent will identify using a system of 9 objects so that the total testing data collected is 60 normal conditions, 60 cacao identified as disease attack condition, and 60 cacao identified as pests attack condition.

Table 1 showed the testing results of the application by using the detection feature. Test results value showed in similarity percentage of true positive. Based on the test

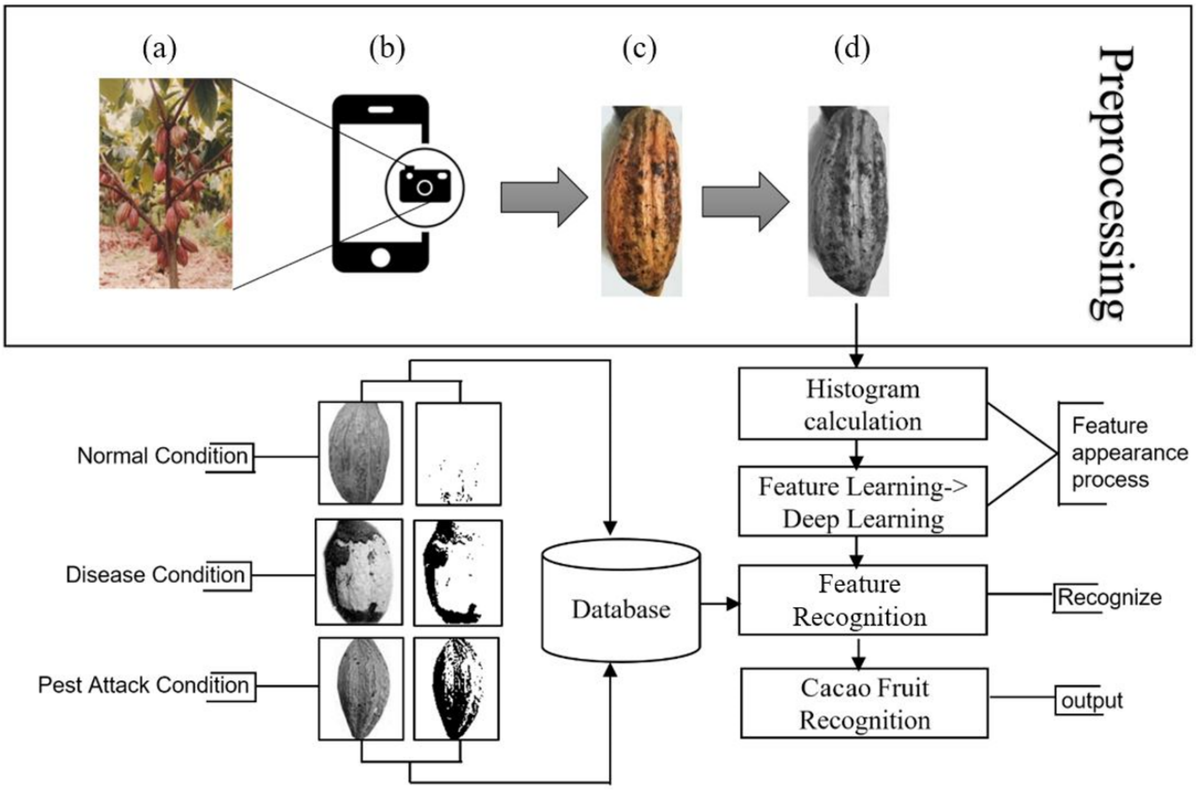


FIGURE 3. Frameworks of the recognition process

results presented, it was found that the feature system was well recognized. Each user determines three cacao fruit objects from each cacao fruit classification. The recap of the test as per the ROC matrix, according to Equation (1) is presented in Table 2.

The accuracy measurement results, as presented in Table 2 show that the value of 100% from 180 testing data, with the similarity of objects to the database, is quite high with an average of above 80%. This result shows that the database created by the tensor flow library with 615 datasets sufficiently represents the features of the cacao fruit object in all three classifications. Three classifications of cacao fruit objects show that the developed application has excellent performance and is ready to be used on plantations by cacao farmers. Screenshot sample of the application testing results, as shown in Figure 4 shows the display of recognition results recommended by the application based on a database processed by the deep learning algorithm.

In part (a), the object identified by the expert is stated as a normal fruit condition with the highest percentage of similarity in the normal classification (93.43%), while the other two classifications are far different. Following the system developed in the next section of the report will provide recommendations based on the highest similarity. Likewise, part (b) identified by experts stated as a condition of the disease with the highest percentage of similarity in disease (97.97%), while the other two classifications are also very different. Whereas in section (c), the experts identified were stated as being attacked by pests with the highest percentage of similarity in pest classification (77.81%). Although the percentage of pests is small compared to the others, the other two classifications are far different.

6. **Conclusions.** We proposed a mobile application with deep learning algorithm integration in database recognition. The development of the system is designed to produce an expert system based on image processing with a mobile platform that can be used in real time at a cacao plantation location. System accuracy measurements showed satisfactory

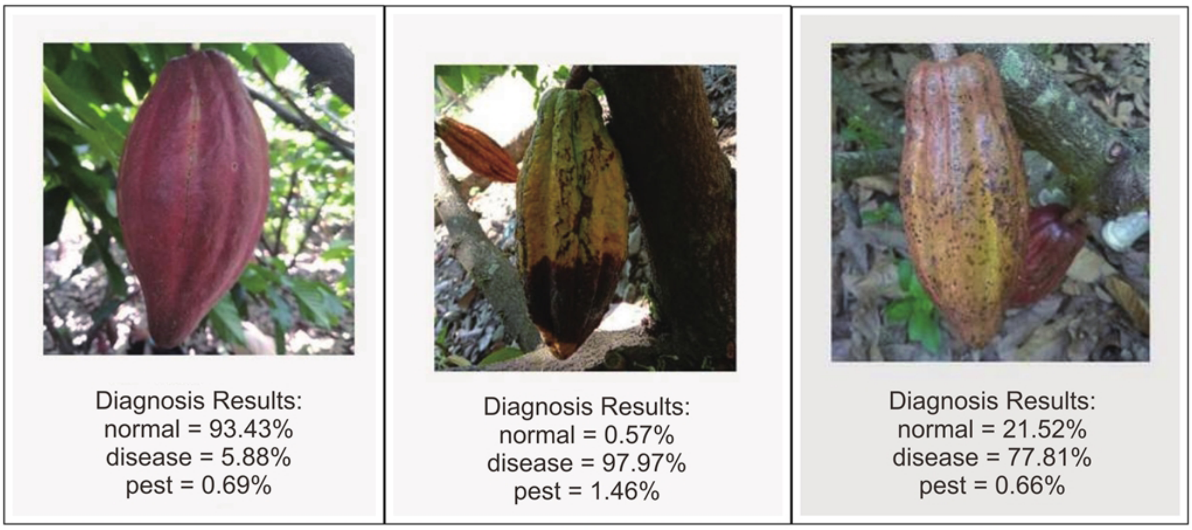
TABLE 1. Testing result

User	Mobile phone type	Android version	Camera specification	Object (%) N-1st	N-2nd	N-3rd	D-1st	D-2nd	D-3rd	P-1st	P-2nd	P-3rd
User 1	Vivo Y55	6.0.1	8 MP	94.32	75.76	89.98	78.13	88.07	76.95	86.96	86.39	82.32
User 2	Oppo a3s V5.1	8.1.0	13 MP	96.93	75.15	75.17	88.85	78.30	91.41	82.88	83.10	71.86
User 3	Vivo Y21	5.1	5 MP	87.04	72.25	71.75	92.95	72.26	78.52	76.42	81.55	76.58
User 4	Oppo A71	7.1.1	13 MP	91.64	92.09	83.39	74.84	74.29	86.85	79.77	89.65	72.38
User 5	Oppo A5	9	12 MP	86.76	88.74	83.15	80.04	76.77	82.22	91.39	72.81	73.68
User 6	xeomi Retmi 2	8.1.0	14 MP	82.27	82.07	70.97	77.93	83.76	77.82	76.27	90.25	75.97
User 7	Oppo A3s	8.1.0	13 MP	94.81	95.84	72.79	89.46	87.67	78.48	91.50	82.80	71.86
User 8	Oppo A37	V.5.1	8 MP	94.81	95.34	72.19	89.46	87.07	78.48	91.50	82.80	71.86
User 9	Vivo Y 51L	5	8 MP	84.59	75.04	71.81	93.69	89.46	80.76	87.17	88.41	80.45
User 10	Vivo Y81	8.1.0	13MP	85.76	85.91	91.85	99.28	92.29	94.75	81.91	77.13	78.72
User 11	Vivo Y53	6.0	8 MP	81.15	96.24	95.53	96.97	77.59	76.42	92.73	71.31	85.94
User 12	Vivo Y12	9	13 MP	78.33	87.60	78.34	72.64	87.16	94.43	93.45	82.14	80.14
User 13	Oppo A3s	8.0.1	13 MP	82.73	95.95	83.15	80.59	96.79	92.41	82.42	80.79	88.67
User 14	Samsung J1 ace	5	5 MP	79.35	73.90	88.34	91.02	89.00	88.74	83.93	95.32	72.45
User 15	Vivo Y12	9	13 MP	81.57	73.10	73.72	82.65	82.22	97.97	80.24	77.29	71.52
User 16	Asus Pro m1	9	15 MP	93.43	74.41	80.41	86.86	80.70	94.26	83.32	75.74	75.34
User 17	Samsung j2prime	6	8 MP	87.67	81.98	71.15	71.45	80.44	77.65	82.78	96.05	79.09
User 18	Vivo Y91	8.1.0	13 MP	84.79	75.16	71.79	86.34	74.24	90.65	71.15	82.80	71.80
User 19	Huawei SCL-L21	5.1	8 MP	83.36	93.94	91.48	71.79	79.12	88.27	77.81	76.46	72.70
User 20	Asus Max pro M1	9	15 MP	81.33	91.24	93.43	98.91	91.44	92.54	73.78	83.32	71.05
Average				**86.63**	**84.09**	**80.52**	**85.19**	**83.43**	**85.98**	**83.37**	**82.81**	**76.22**

N = Normal Condition, D = Disease Condition, P = Pest Condition, MP = Mega Pixel

TABLE 2. Performance results

Performance type (Average)	N (%)	D (%)	P (%)
Accuracy	100	100	100
Similarity	83.75	84.87	80.80



(a) (b) (c)

Figure 4. Sample screenshot of cacao's fruits condition identification

results with recognition of 100% in each object classification of cacao fruit with a similarity database for normal classification of cacao fruit by 83.75%, 84.87% for disease attack condition, and pest attack condition by 80.80%. The previous image processing algorithm has also been implemented, but in terms of accuracy and computational complexity, it has been improved in the development of the application model with the integration of the deep learning algorithm. Future study will develop a system that integrates identification applications with the latest news updates related to cacao cultivation and develop a cross-platform system that can meet together between cacao experts and farmers in focus consultation.

Acknowledgment. Many thanks for the research team at the Research Laboratory of Universitas Al Asyariah Mandar, Artificial Intelligence Laboratory of Universitas Hasanuddin and Ministry of Research, Technology, and Higher Education of Republic Indonesia under F. Number 115/SP2H/LT/DRPM/2019.

REFERENCES

[1] D. S. Prabha and J. S. Kumar, Assessment of banana fruit maturity by image processing technique, *J. Food Sci. Technol.*, vol.52, no.3, pp.1316-1327, 2015.
[2] D. S. Tan et al., A method for detecting and segmenting infected part of cacao pods, *DLSU Research Congress*, De La Salle University, Manila, Philippines, 2016.
[3] Basri, Harli, Indrabayu, I. S. Areni and R. Tamin, Image processing system for early detection of cocoa fruit pest attack, *J. Phys. Conf. Ser.*, vol.1244, 2019.
[4] B. Basri, R. Tamin, H. Harli, I. Indrabayu and I. S. Areni, Gabor filter evaluation for binary threshold image processing in early detection application, *Jour. Adv. Res. Dyn. Control Syst.*, vol.10, no.10, pp.2300-2307, 2018.
[5] M. S. Hossain and G. Muhammad, An emotion recognition system for mobile applications, *IEEE Access*, vol.5, pp.2281-2287, 2017.
[6] F. Ding, Complexity, convergence and computational efficiency for system identification algorithms, *Control Decis.*, vol.31, no.10, pp.1729-1741, 2016.
[7] K. K. Pal and K. S. Sudeep, Preprocessing for image classification by convolutional neural networks, *IEEE International Conference on Recent Trends in Electronics, Information & Communication Technology (RTEICT)*, pp.1778-1781, 2016.
[8] A. Chowanda and R. Sutoyo, Convolutional neural network for face recognition in mobile phones, *ICIC Express Letters*, vol.13, no.7, pp.569-574, 2019.
[9] W. Liu, H. Ma, H. Qi, D. Zhao and Z. Chen, Deep learning hashing for mobile visual search, *EURASIP J. Image Video Process.*, vol.2017, no.1, p.17, 2017.

[10] V. Chandrasekhar, G. Takacs, D. Chen, S. Tsai, R. Grzeszczuk and B. Girod, CHoG: Compressed histogram of gradients a low bit-rate feature descriptor, *2009 IEEE Conference on Computer Vision and Pattern Recognition*, pp.2504-2511, 2009.

[11] W.-M. Pang, K.-S. Choi and J. Qin, Fast Gabor texture feature extraction with separable filters using GPU, *J. Real-Time Image Process.*, vol.12, no.1, pp.5-13, 2016.

[12] A. R. Badanidiyoor and G. K. Naravi, $\theta(1)$ time complexity parallel local binary pattern feature extractor on a graphical processing unit, *ICIC Express Letters*, vol.13, no.9, pp.867-874, 2019.

[13] C.-H. Wu, C.-C. Lai, H.-J. Lo and P.-S. Wang, A comparative study on encoding methods of local binary patterns for image segmentation, *International Conference on Smart Vehicular Technology, Transportation, Communication and Applications*, pp.277-283, 2018.

[14] T. Fawcett, An introduction to ROC analysis, *Pattern Recognit. Lett.*, vol.27, no.8, pp.861-874, 2006.

[15] N. A. Obuchowski, ROC analysis, *Am. J. Roentgenol.*, vol.184, no.2, pp.364-372, 2005.

[16] H. Rathore, A. K. Al-Ali, A. Mohamed, X. Du and M. Guizani, A novel deep learning strategy for classifying different attack patterns for deep brain implants, *IEEE Access*, vol.7, pp.24154-24164, 2019.

[17] D. K. Shin, M. U. Ahmed and P. K. Rhee, Incremental deep learning for robust object detection in unknown cluttered environments, *IEEE Access*, vol.6, pp.61748-61760, 2018.

[18] Z.-M. Fang and Z.-M. Lu, Deep belief network based finger vein recognition using histograms of uniform local binary patterns of curvature gray images, *International Journal of Innovative Computing, Information and Control*, vol.15, no.5, pp.1701-1715, 2019.