Cholissodin, I., Sutrisno, S., Soebroto, A.A., Novita, H.D., Murlistyarini, S., Suwito, G.A. and Hidayat, N., 2022. Development of Computational Medical Imaging Using Convolutional Neural Network Improved by Time-varying Particle Swarm Optimization and Extreme Learning Machine. Proceedings or Program Book of the Brawijaya International Conference (BIC) on Science & Technology for Global Disaster & Resilience, series 6, pp.5. https://bic-series.ub.ac.id/bic-stgdr/

Development of Computational Medical Imaging Using Convolutional Neural Network Improved by Time-varying Particle Swarm Optimization and Extreme Learning Machine

I Cholissodin[1,*], S Sutrisno[1], A A Soebroto[1], H D Novita[2], S Murlistyarini[2], G A Suwito[1] and N Hidayat[1]

[1]Faculty of Computer Science, Brawijaya University Jl. Veteran Malang, Jawa Timur 65145, Indonesia.
[2]Faculty of Medicine, Brawijaya University Jl. Veteran Malang, Jawa Timur 65145, Indonesia.

[*]E-mail: *imamcs@ub.ac.id*

Abstract. Eyes and skin require highly intensive care. The obstacle that is often encountered by a person in maintaining the health of these two organs, however, is the lack of understanding regarding how to know and identify the health conditions of those two. This definitely becomes such a problematic issue for someone that it requires an easy, fast and precise handling. Another obstacle that is frequently faced is the difficulty in distinguishing the characteristics of eye and skin diseases that are visually very similar. Therefore, to overcome this problem, we need the right technology to identify and facilitate a patient or the public so that the diseases are more quickly handled to get the healing solutions. The main step in identifying the disease is to read the image data and then do the preliminary processing to clarify and improve the quality of the image as the input data using filtering methods. Convolutional Neural Network (CNN) is a part of Deep Learning (DL) method was selected as the data learning that is carried out by applying certain methods to the training image data in accordance with the research that has been performed. In this study, the detection system was made using Improve DL with Time-varying inertia weight (TVIW) and Time-varying acceleration coefficients (TVAC) Particle Swarm Optimization (PSO) and Extreme Learning Machine (ELM) that resulted in the accuracy of 83.1683%. This result is considered to be optimal enough and can be used by medical teams in hospitals or clinics as a consideration.

Keywords:
medical imaging, convolutional neural network, improve deep learning, particle swarm optimization, extreme learning machine

1. Introduction

Vision is an invaluable gift given by God. Eyes have a very important function in life. At present, there are variety of eye disorders. In 1993-1996, 1.5% of Indonesia's population experienced blindness that was caused by cataracts (52%), glaucoma (13.4%), refractive abnormalities (9.5%), retinal disorders (8.5%), corneal abnormalities (8.4%), and other eye diseases [1]. Cataract is a disease that many people suffer because it cannot be prevented but can be treated through rehabilitation. The main cause of blindness in Indonesia is also cataracts. In a study by Supriyanti (2010), cataract screening has been performed by utilizing a mirrorless digital camera and smartphones using extraction methods based on color channel and texture analysis that produce software and hardware. The screening was tested in environments at indoor, semi-outdoor, and outdoor conditions, with SVM as the classification method to identify serious and non-serious types of cataracts, in areas with finite health equipment facilities. Afterwards, the results of the classification is evaluated by using ROC Curve value [2] [3]. One of the factors that cause cataracts is age [4]. In addition to age, it can also be caused by proteins that clot in the eye lens so that the lens, which is originally clear, is slowly turning to a yellowish brown color [5]. Moreover, the other factors for cataract are having too frequent exposure to sunlight, suffering certain diseases, consuming alcohol, having unhealthy diet, and smoking [6]. To date, there are around 1 million blind people due to cataracts resulting from the Rapid Assessment of Avoidable Blindness (RAAB) method with an average blindness rate of 3% for residents over the age of 50 years in Indonesia [4].

Skin is a layer on the surface of the body the main function of which is as the protector from a variety of external irritation and stimuli. Skin of body organs will reflect one's health and beauty. Therefore, it is very essential to maintain and care for skin health, especially the facial skin to avoid premature aging [7]. Skin aging is triggered by various factors, such as lifestyle, diet, heredity, and other personal habits. As an example, smoking can produce free radicals [8]. In 2016 data, by determining the prevalence of the aging process in adolescents aged between 18-21 years, it was found that they experienced premature aging by 57.35% [9]. In 2010, Zhang, et al. mentioned that the role of skin was to protect and deter external irritation and regulate water levels in the body so that it does not lack and excess the required amount. This role is carried out by the Stratum Corneum (SC) layer that contains dead cells (corneocytes) which are embedded in the lipid matrix. Water content in the SC plays an important role in regulating skin health. Thus, many dermatologist are interested to measure the water content in SC. Basically, the technique for measuring the water content in SC is based on measuring electricity-based parameters, for example using a Corneometer to assess epidermis hydration, which is already used widely. However, the technique only measures the water content indirectly. As a result, this measurement can be influenced by parameters that are not related to water content such as ions available in the product which can cause electrical potential or other factors [10].

Hitherto, several methods in the classification of eyes and skin that are often used are Support Vector Machine [11], Learning Vector Quantization (LVQ) [12], Adaptive Single Gaussian (ASG) [13], and Fuzzy C-Means [14]. In order to improve the accuracy of the classification results, there is another popular employed method, i.e. Deep Learning (DL), which is contained in Neural Network (NN). Nonetheless, DL is often not fast enough in determining the results of classification because there is repetitive learning in DL; hence, it is necessary to use techniques that are able to accelerate the speed in the classification to be more optimal. Extreme Learning Machine (ELM) algorithm has the effectiveness in solving classification problems with high accuracy values when compared to Support Vector Machine (SVM) algorithm [15]. Consequently, this research proposes the use of Improve Deep Learning method by utilizing Extreme Learning Machine (ELM) in the hope that the detection of eye and skin health can be more accurate and faster by adding Particle Swarm Optimization (PSO) algorithms to optimize some parameters of Deep Learning algorithm.

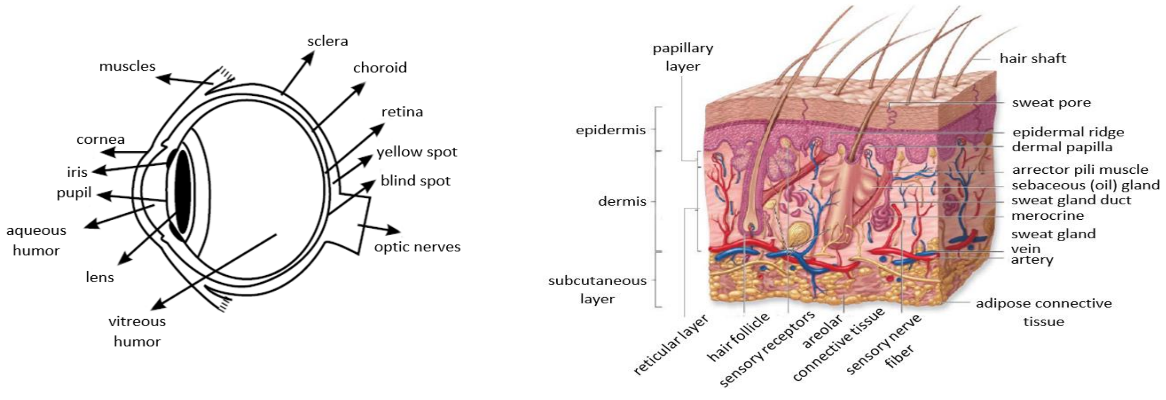
2. Methods

2.1. Human Eyes and Skin

Eyes are one of the sensory organs of the human which serve to see and consist of muscles, sclera, choroid, retina, yellow spot, blind spot, optic nerves, vitreous humor, lens, aqueous humor, pupil, iris and cornea. A person's vision is very much determined by the refraction of light in the eye. If there is an abnormal refraction of light in the eye, then the object that we see is less clear (farsightedness) due to the imprecise point of light on the retina [16]. In 1993-1996, 1.5% of the population in Indonesia experienced blindness that was caused by cataracts (52%), glaucoma (13.4%), refractive abnormalities (9.5%), retinal disorders (8.5%), cornea disorders (8.4%) and other eye diseases [1]. In 2014-2019, through Global Action Plan (GAP), in Indonesia, according to the latest survey of blindness called Rapid Assessment of Avoidable Blindness (RAAB), which is a standard data collection of blindness and visual impairment set by WHO, the survey of which is based on the population of people with blindness, visual impairment, and eye care services for people aged 50 years and over, the results revealed a blindness prevalence of 3%, and the highest cause of blindness is cataract.

The skin is a layer on the surface of the body the main function of which is as the protector from a variety of external irritations and stimuli. The skin of the entire body of an adult, accounting for about 15% of total body weight, consists of three layers: epidermis, dermis, and subcutaneous tissue. The thickness of each skin layer varies greatly, usually depending on the location of the anatomy of the human body [17]. The skin of human organs becomes the reflection of one's health and beauty. Therefore, it is very essential to maintain and care for skin health, especially the facial skin to avoid premature aging [7]. Human skin is divided into two layers, i.e. the epidermis layer that is composed of epithelial tissue originating from the ectoderm and the dermis layer that comes in the form of connective tissue originating from the mesoderm [18]. The balance of skin hydration (moisture) and sebum (skin surface lipids) is considered a major factor in skin health. This balance makes the skin have a radiant, smooth texture and affects the aging condition of the skin. The device used for the measurement of these factors is called Corneometer CM820, Nova DPM 9003 that has to be in contact with the skin. The measurement result is usually affected by the amount of electrolytes, contact area, applied pressure and sensitiveness to external temperatures and humidity [19].

The condition of epidermal barrier of the skin is influenced by the amount of sebum, epidermal hydration, transepidermal water loss, and pH gradient between the surface of the skin and the inside of the body. Other influencing factors are for example age, sex, race, skin anatomy area, sweat intensity, skin temperature and ambient temperature, humidity, year season, rhythm of daily activities, hormonal balance, and others. The surface of the cornified layer of the skin is covered by a lipid film as an epidermal barrier. This lipid film comes from two sources, which are sebum that is secreted by the sebaceous glands, which are the largest part of the lipid mantle, and epidermal lipids. The thickness of the mantle lipids ranges from 0.5 μm to 5 μm, depending on the number of sebaceous glands. The surface of healthy skin is characterized by the amount of acidic pH oscillating between 4.0 and 6.0. The hydration value of the epidermis varies greatly and depends on the location of the anatomy of the body. The highest value can be found on the facial skin of articular fossae, the lower value is in the forearm, while the lowest is in the shins. This largely depends on the thickness of the epidermal layer and the location of the sebaceous glands and sweat. Meanwhile, the skin humidity can also vary, depending on vicinity humidity, for example from ambient temperature and the environment [20]. The anatomical image of the human eye can be observed in Figure 2.1a and the anatomy of the human skin is in Figure 2.1b.



(a) (b)

Figure 1. Anatomy of the Human Eye and Skin

2.2. Improve CNN for Classification

CNN of Deep Learning algorithm with PSO can be utilized to predict rainfall in Malang regency at our previous research (Deep Learning for Prediction), the work of which used feature extraction and data transformation into image form. The amount of convolution and pooling layer depends on the complexity of the case. Convolution layer consists of several groups of features and pooling layer consists of a reduction or summary of several groups of features [21]–[26]. Here are the detailed steps of Deep Learning with PSO:

- Prepare map / architecture DL-ELM with PSO, or using VGG, Inception and others.
- Set Parameter value.
- Deep PSO Process
  The representation of 4 dimensional clusters on each PSO particle in Hybrid PSO-DLNN (Deep PSO) can be seen in Table 1.

Table 1. Representation of PSO Particles for Deep Learning

$x_i(t)$	*k*	*FC1_Wjk*	*FC2_Wjk*	*FC3_Wjk*

In this step include Training Process of CNN-ELM and Testing Process of CNN-ELM, where,
k consists of 1 dimension = [*Kmin*=1;*Kmax*=5]. When calculating DL,
k will be converted to 2**k* + 1.
FC1_Wjk consists of 1 x (5 x 7) = [-0.5;0.5]
FC2_Wjk consists of 1 x (7 x 7) = [-0.5;0.5]
FC3_Wjk consists of 1 x (4 x 7) = [-0.5;0.5]

3. Design and Implementation

In our research, the design and implementation is started by initial steps to carry out the process of data collection are as follows:

- Crawl the data from Google with the keyword "normal eyes as in Fig. 2, cataract eyes, healthy skin, dry skin" with the following command on Jupyter Notebook by command below

```
!googleimagesdownload --keywords " normal eyes" --limit 50 --chromedriver
C:\Users\Imamcs\Downloads\chromedriver_win32\chromedriver.exe
```

(a) (b)

Figure 2. Crawling code and sample results (a. cataract, b. normal)

- Crop the image as in Fig. 3

(a) (b) (c) (d)

Figure 3. Crawling code and sample results (c. dry skin, d. healthy skin)

- Performing Pseudocode Deep PSO based on Fig. 4

```
begin

      t = 0
      initialization
           position (xij(t)) and count fitness each particle, velocity (vij(t)=0),
           Pbestij(t) = xij(t),
           and Gbestgj(t), where xij(t) is represent from Table 1.

       do
           t = t + 1
           update velocity (vij(t))
           vij(t) = w.vij(t-1)+c1.r1.(Pbestij(t-1)- xij(t-1))+c2.r2.(Gbestgj(t-1) -
                    xij(t-1))
          update position (xij(t)) and then count fitness each particle
          xij(t) = xij(t-1)+ vij(t))
          update Pbestij(t) and Gbestgj(t)
      while (not a termination condition)

end
```

Figure 4. Pseudocode Deep PSO

4. Results and Discussion

In testing the core engine, this research used convergence observations of accuracy values obtained in each experiment. The complete code of the BackEnd prototype implementation of “Detection of Eye and Skin Health by Improve Deep Learning based on Convolution Neural Network and Extreme Learning Machine” has been uploaded to github and can be downloaded at the link of https://github.com/imamcs19/Improve-Deep-Learning-With-PSO-For-Classification that includes a dataset for the training and testing process which begins with the conversion of image data into a dataset with a certain resized dimension.

From the test results starting in Figure 5, which refers to the data crawling showed a significant increase in accuracy. The different test scenarios used in the real data utilized variations in resized values for the dimensions of the employed dataset, starting from [32 x 32] with the highest accuracy of 83.1683%. From the results of the real data testing, it can be concluded that the dimension of the input resized image has a significant effect on the results of accuracy, which shows the pattern that the greater the resized dimensions, the higher the accuracy value obtained even though the iteration used is still not large enough for the good training process. Nevertheless, the results of all tests have shown a convergence pattern of accuracy values from every different trial session. The training process produces parameter values that are optimized from the Deep Learning parameters by the Particle Swarm Optimization (PSO) algorithm that is stored on Gbest.mat on the crop. In a deeper elaboration, then each PSO particle contains four (4) types of optimized parameters that later can be used again during the testing process as the production of the core engine that leaves the testing process only; thus, the processing time is much faster when compared to the training process.

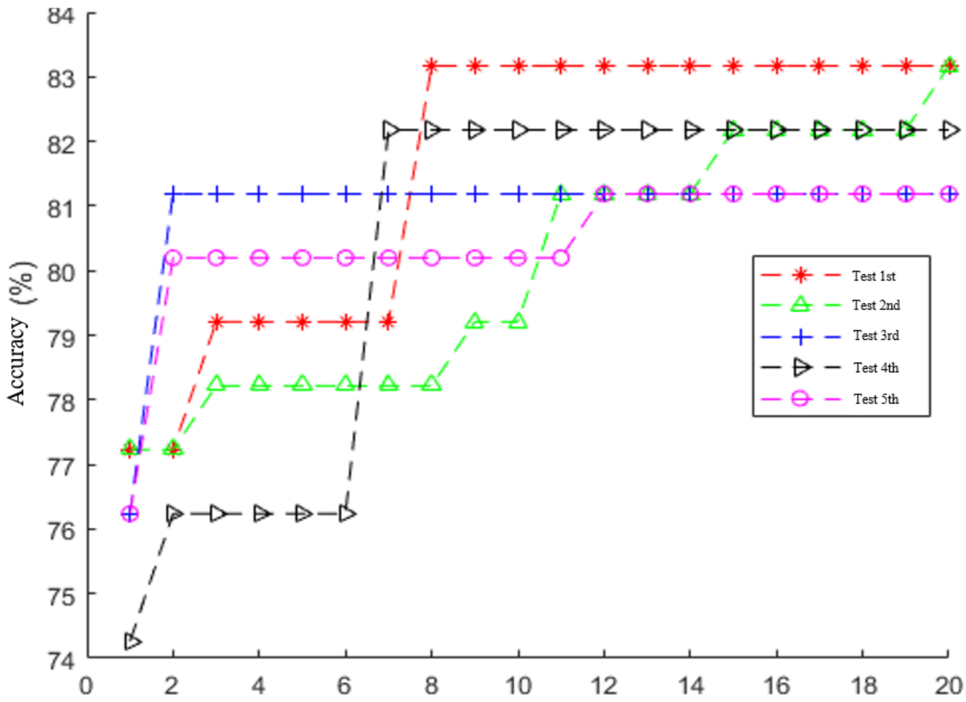


Figure 5. Deep PSO - Convergence Test Results

5. Conclusion

The implementation of the system has been successfully carried out by combining several components of the algorithm devices, starting from preprocessing, implementing improve deep learning based on Convolution Neural Network (CNN) and Extreme Learning Machine (ELM) with Particle Swarm Optimization (PSO) for classification, to calculating the accuracy of the test results. Based on the final result of the implementation process of Improve Deep Learning algorithm, the accuracy obtained was 83.1683 %. This result can be considered very good in terms of the performance of the training process of the testing process. This research only focuses on small data and uses crawling data from Google. Therefore, it is expected that further research can use more data directly from several hospitals or health clinics. In addition, the next research are also able to collect and develop many variant data like covid-19 dataset or others also create smart devices to propose as an affordable industrial commodity to be tested by several health experts in clinics, hospitals, and other health institutions before it is mass-produced.

References

[1] P. Kemenkes, “Gangguan Penglihatan Masih Menjadi Masalah Kesehatan,” Mar. 11, 2010. https://www.kemkes.go.id/article/view/845/gangguan-penglihatan-masih-menjadi-masalah-kesehatan.html (accessed Nov. 25, 2022).

[2] R. Supriyanti, “Cataract Screening Techniques under Limited Health Facilities,” 発展途上国のための白内障スクリーニング技術, Mar. 2010, doi: 10.34413/dr.00898.

[3] Z. Q. Ik, S. L. Lau, and J. B. Chan, "Mobile cataract screening app using a smartphone," in *2015 IEEE Conference on e-Learning, e-Management and e-Services (IC3e)*, Aug. 2015, pp. 110–115. doi: 10.1109/IC3e.2015.7403496.

[4] P. Kemenkes, "Jumlah Penderita Katarak di Indonesia Tinggi, Menkes Ingatkan Perilaku Hidup Sehat," *Direktorat P2PTM*, Nov. 05, 2018. https://p2ptm.kemkes.go.id/kegiatan-p2ptm/pusat-/jumlah-penderita-katarak-di-indonesia-tinggi-menkes-ingatkan-perilaku-hidup-sehat (accessed Nov. 25, 2022).

[5] F. Nurin, "Katarak," *Hello Sehat*, Jul. 26, 2021. https://hellosehat.com/mata/katarak/mata-katarak/ (accessed Nov. 25, 2022).

[6] M. Nareza, "Katarak Pada Lansia," Sep. 08, 2021. https://www.alodokter.com/katarak-pada-manula (accessed Nov. 25, 2022).

[7] R. Andriana, "Minat Konsumen terhadap Perawatan Kulit Wajah dengan Metode Mikrodermabrasi di Viota Skin Care Kota Malang," Jan. 2014, Accessed: Nov. 25, 2022. [Online]. Available: https://ejournal.unesa.ac.id

[8] R. Widyawinata, "Penuaan Kulit (Skin Aging)," *Hello Sehat*, Aug. 05, 2021. https://hellosehat.com/penyakit-kulit/kulit-lainnya/penuaan-kulit/ (accessed Nov. 25, 2022).

[9] M. Dewiastuti and I. F. Hasanah, "Pengaruh Faktor-Faktor Risiko Penuaan Dini di Kulit Pada Remaja Wanita Usia 18-21 Tahun," vol. 10, no. 1, pp. 21–25, May 2016.

[10] G. Zhang, A. Papillon, E. Ruvolo Jr., P. R. Bargo, and N. Kollias, "In vivo comparative documentation of skin hydration by confocal Raman microscopy, SkinSensor, Skicon, and NovaMeter," vol. 7548, p. 75480M, Feb. 2010, doi: 10.1117/12.848215.

[11] C. Florea, M. Moldovan, M. Gordan, A. Vlaicu, and R. Orghidan, "Eye color classification for makeup improvement," in *2012 Federated Conference on Computer Science and Information Systems (FedCSIS)*, Sep. 2012, pp. 55–62.

[12] R. Hariyanto, A. Basuki, and R. N. Hasanah, "Klasifikasi Penyakit Mata Katarak Berdasarkan Kalainan Patologis Dengan Menggunakan Algoritme Learning Vector Quantization," *Netw. Eng. Res. Oper.*, vol. 2, no. 3, Art. no. 3, Nov. 2016, doi: 10.21107/nero.v2i3.63.

[13] S. Bianco, F. Gasparini, and R. Schettini, "Adaptive Skin Classification Using Face and Body Detection," *IEEE Trans. Image Process.*, vol. 24, no. 12, pp. 4756–4765, Dec. 2015, doi: 10.1109/TIP.2015.2467209.

[14] J. Lee, Y. Chen, L. Liu, and C. Huang, "A Facial-Skin Condition Classification System Using Texture and Fuzzy C-Means Technologies," in *Fourth International Conference on Fuzzy Systems and Knowledge Discovery (FSKD 2007)*, Aug. 2007, vol. 4, pp. 127–131. doi: 10.1109/FSKD.2007.22.

[15] L. Zhang and D. Zhang, "SVM and ELM: Who Wins? Object Recognition with Deep Convolutional Features from ImageNet," Jun. 2015, doi: 10.48550/arXiv.1506.02509.

[16] S. Saminan, "Efek Penyimpangan Refraksi Cahaya Dalam Mata Terhadap Rabun Dekat Atau Jauh," Aug. 28, 2013. https://garuda.kemdikbud.go.id/documents/detail/1794315 (accessed Nov. 25, 2022).

[17] P. A. J. Kolarsick, M. A. Kolarsick, and C. Goodwin, "Anatomy and Physiology of the Skin," *J. Dermatol. Nurses Assoc.*, vol. 3, no. 4, pp. 203–213, Aug. 2011, doi: 10.1097/JDN.0b013e3182274a98.

[18] S. J. R. Kalangi, "Histofisiologi kulit," *J. BiomedikJBM*, vol. 5, no. 3, Art. no. 3, 2013, doi: 10.35790/jbm.5.3.2013.4344.

[19] A. Ezerskaia, S. F. Pereira, H. P. Urbach, R. Verhagen, and B. Varghese, "Quantitative and simultaneous non-invasive measurement of skin hydration and sebum levels," *Biomed. Opt. Express*, vol. 7, no. 6, pp. 2311–2320, May 2016, doi: 10.1364/BOE.7.002311.

[20] M. Boer, E. Duchnik, R. Maleszka, and M. Marchlewicz, "Structural and biophysical characteristics of human skin in maintaining proper epidermal barrier function," *Postepy Dermatol. Alergol.*, vol. 33, no. 1, pp. 1–5, Feb. 2016, doi: 10.5114/pdia.2015.48037.

[21] I. Cholissodin, S. Sutrisno, A. A. Soebroto, L. Hanum, and C. A. Caesar, "Optimasi Kandungan Gizi Susu Kambing Peranakan Etawa (PE) Menggunakan ELM-PSO Di UPT Pembibitan Ternak Dan Hijauan Makanan Ternak Singosari-Malang," *J. Teknol. Inf. Dan Ilmu Komput.*, vol. 4, no. 1, Art. no. 1, Feb. 2017, doi: 10.25126/jtiik.201741223.

[22] I. Cholissodin and S. Sutrisno, "Prediction of Rainfall using Simplified Deep Learning based Extreme Learning Machines," *J. Inf. Technol. Comput. Sci.*, vol. 3, no. 2, Art. no. 2, Nov. 2018, doi: 10.25126/jitecs.20183258.

[23] I. Cholissodin, A. A. Soebroto, and S. Sutrisno, "Audit System Development for Government Institution Documents Using Stream Deep Learning to Support Smart Governance," *J. Inf. Technol. Comput. Sci.*, vol. 4, no. 1, Art. no. 1, Jun. 2019, doi: 10.25126/jitecs.20194173.

[24] A. A. Soebroto, I. Cholissodin, M. T. Frestantiya, and Z. E. Arief, "Integration Method of Local-global SVR and Parallel Time Variant PSO in Water Level Forecasting for Flood Early Warning System," *TELKOMNIKA Telecommun. Comput. Electron. Control*, vol. 16, no. 3, Art. no. 3, Jun. 2018, doi: 10.12928/telkomnika.v16i3.6772.

[25] G.-B. Huang, Q.-Y. Zhu, and C.-K. Siew, "Extreme learning machine: a new learning scheme of feedforward neural networks," in *2004 IEEE International Joint Conference on Neural Networks (IEEE Cat. No.04CH37541)*, Jul. 2004, vol. 2, pp. 985–990 vol.2. doi: 10.1109/IJCNN.2004.1380068.

[26] I. Cholissodin and E. Riyandani, *Buku Ajar Swarm Intelligence*. 2016.