

Malaria cell detection using deep learning techniques and Investigation on efficacy and safety of carica papaya leaf extract on malaria

B Uma Maheswari¹, S. V. Chiranjeevi², C. Sushama³, S. Venkataramana⁴, D Naga Malleswari⁵

¹Associate Professor, Department of Networking and Mobile Application, PSG College of Arts & Science, Coimbatore, TN, India

²Assistant Professor, Department of CSE, N.B.K.R Institute of Science and Technology, Vidyanagar, Nellore, AP, India

³Associate Professor, Department of CSE, Sree Vidyanikethan Engineering College, Tirupati, AP, India.

⁴Professor, Department of Information Technology, SRKR ENGINEERING COLLEGE, Chinamiram, Bhimavaram-534204, Andhra Pradesh-India.

⁵Associate Professor, Koneru lakshmaiah Education Foundation, Vaddeswaram, Guntur, AP, India

Email: umasharan7@gmail.com

DOI: 10.47750/pnr.2022.13.S01.07

Abstract

Malaria is a serious fever infection caused by Plasmodium parasites, which individuals get by bites from female Anopheles mosquitoes carrying the disease. 50% of the world's population impacted by malaria in 2020. People with HIV/AIDS, pregnant women, young children under 5, infants, and those moving to areas where malaria transmission is higher but immunity is lower, such as travellers, mobile communities, and migrant workers, are more likely to contract malaria and develop serious illnesses. Despite these figures, an early, accurate diagnosis can lower the fatality rate from malaria. Numerous factors, including a severe lack of experienced specialists in village areas, improper information management, the use of fake medications, the accessibility of affordable diagnostic tools, global warming, and many others, contribute to the development in malaria and their unnatural geographic location. Malaria is a complicated, fast spreading infectious illness that has become difficult to manage due to the prevalence of its parasites. It is difficult to distinguish between blood smear microscopic images of parasite- and non-parasite-infected blood due to malaria. We have created an automated solution using deep learning methods to address this difficulty. Additionally, the effectiveness and safety of papaya leaf extract from Carica papaya on malaria were examined.

Keywords: malaria; fever; death rate; severe; visual inception; CAD; fast; deep learning; detection; parasites; blood smear images; automated; efficacy; safety; papaya leaf extract.

1. INTRODUCTION

In fact, Plasmodium parasites, that people get by bites from female Anopheles mosquitoes carrying the disease, are the cause of severe fever illness called malaria. Of five parasite species that lead to malaria in people, *P. vivax* and *P. falciparum* have become most hazardous. *P. falciparum* are the most prevalent and dangerous malaria parasite on the Africa continent. *P. vivax* are the most prevalent malaria parasite found outside of Africa.

Malaria's earliest symptoms, such as chills, headache, fever might be mild and hard to detect. Ten to fifteen days after the infected insect bite, they normally develop. Without treatment, *P. falciparum* malaria can progress to severe illness and deaths in much less than 24hrs.

In 2020, 50% of the global population affected from malaria. AIDS persons, pregnant women, kids under 5, Infants, and people migrating to places with higher malaria transmission but lower immunity, including travelers, mobile communities, migrant workers were at increased chance of catching malaria and the emergence of serious illness [1].

Despite these figures, an early, accurate diagnosis can lower the fatality rate from malaria. Numerous factors, including a severe lack of experienced specialists in village areas, improper information management, the use of fake medications, the accessibility of affordable diagnostic tools, global warming, and many others, contribute to the development in malaria and their unnatural geographic location [2]. Due to the number of malaria parasites, this infectious disease has grown difficult to control and is complex and rapidly spreading. Malaria detection is challenging and makes it impossible to distinguish between parasite- and non-parasite-infected blood smear microscopic (BSM) pictures.

The challenge for researcher is to achieve efficient findings of infectious parasite identification with the least amount of time, money, and effort. The idea, visual inspections have evolved in field of machine aided diagnosis in recent decades, acting as a new approach to helpful software in clinical medical imaging and decision support. However, manual examination of this widespread condition was irrational, time taking, vulnerable to error. One of the well-known essential issues to distinguish stain BSM picture components, is visual process of describing to detect malaria parasite. Standard method of diagnosing malaria in a clinic was the laborious, time-consuming task that has a low likelihood of producing an accurate result [2].

The environment and a pathologist's workload both contribute to a rise in malaria cases, leading to inadequate health care services. A better objective evaluation for individualized healthcare and diagnosis tasks has been made possible by computer-aided diagnosis (CAD), taking into account the aforementioned significant limitations. With adequate time series management, the advancement of CAD has effectively closed gap in overall image content and local discriminative appearance.

By annotating imaging data sets and identifying anomalies across a diverse range of environmental conditions, the adoption of CAD have the significant influence on every individuals, imaging modalities. CAD has issues related to the intensity fluctuations, shape, size in the image process of the cellular constituents in BSM images [2]. However, the massive amount of unlabeled datasets produced by diagnostic practice combined with the difficulty of detection of malaria parasite in BSM images and "anisotropic voxel size" necessitate creation of CAD models to detect malaria a challenging thing in machine vision [3,5].

Large unlabeled static and dynamic samples and the restricted availability of annotated malaria picture data make this problem incredibly difficult to solve [2]. Therefore, the concept of deep learning emerges here with record-breaking ingenious techniques on algorithms that may assist in detecting malaria parasites in a BSM image regardless of their location [3,4,6,7].

2. Related work

The use of an interacting robot for authentication and authorization while limiting access to personal information stored in the cloud was suggested by Zhang et al. [8]. They presented a fresh cognitive IoT paradigm employing cognition cloud computing in a later endeavour [9]. Additionally, a group of academics [10] presented the Mech-RL module for creating an advisor literary consultant and an unique meta-path teaching channel. In addition, there is some research [11-14] aimed at creating methodologies on communications and information technology to deliver various services related like content recommendation, IoT based home security[15] [16], and network amenity services [17]. These studies are comparable to battery-operated smartphone app to detect malaria which could quickly utilized to IoT edged devices.

Smartphone app created by researchers in [18] uses images of blood samples to quickly identify malaria. We can evaluate blood samples without enlisting the help of microscopy technicians by using a mobile app. The program requires mounting a smartphone to the eyepiece of a microscope. It then analyses photos of a blood samples and draws the red circle around malaria parasite. Later, the lab employee evaluates the markings. Any machine learning method's effectiveness depends on the extraction of useful features. The majority of computerized diagnosis systems that employ machine learning algorithms to analyze image, rely on manually crafted criteria to decision-making [19–21]. In order to assess the variations in image size, colour, background, angle, and location of interests, the method also requires experience in computer vision. The problems that afflict the hand crafted feature extraction can be successfully addressed by using deep learning models[22][36][38].

Smartphone app called MOMALA [23] was created to fast and inexpensive way for detecting malaria. In the typical slide of blood smear, MOMALA application will find malaria parasite. Blood smears was captured using smartphone cam, which is then used to evaluate the images. The application now relies heavily on heavy, large, and difficult to carry microscopes[37][40].

Deep learning models employ a sequence of successive layers with hidden units that perform nonlinear processing in order to discover hierarchy feature relation in input picture. Lower-level features which were decomposed from greater feature help with non - linear decision, learn complexity, extracting features, and categorization [24]. Additionally, DL models outperform machine learning algorithms like SVM when dealing with greater amounts of data and high computation, making them significantly more scalable [25][41][39].

Over the past few decades, a lot of research has been done utilizing computational techniques to find affordable ways to enable interoperable healthcare [26] and lower illness rates. By way of illustration, Neto et. al. [27] suggested the simulator to replicate epidemiological event in real-time. An image processing approach with five stages was suggested by Kaewkamnerd et al. [28] for the identification and categorization of malaria. Anggraini et al[29] 's application used image segmentation algorithms to separate the backdrop of blood cells.

Rajaraman et al[30] .'s implementation of feature extractors for the categorization of parasitized and unparasitic blood cells using pretrained CNN-based deep learning models also makes illness detection easier[45][43]. Utilizing the underlying data, the research employed an experimental strategy to choose the best model layers. 3 convolution layers and 2 fully linked dense

layers make up CNN model. Feature extraction performance is tested by ResNet-50, DenseNet-121, Xception, AlexNet, VGG-16 were isolated from parasitized, and healthy blood cell, respectively[30]. Liang et. al. [32] and Kumar et. al. [31] solely offer CNN-based malaria classifiers[42][44].

3. Methodology

System overview diagram displays deep learning strategy for determining if the sample picture contains pathogens or not, as illustrated in figure 1.

3.1 Acquisition and preprocessing of an image dataset

The methodology for this study starts with the collecting of photographs of blood smears from malaria-infected or malaria-uninfected individuals. a dataset of 27,558 cell pictures in total, divided into two groups of cells—those with and without malaria diseases—that number 27,558 in total [33]. Sample infected and uninfected images were shown in figure 2 and figure 3. All of the photos in the collection were resized to 224x224 pixels.

3.2 Feature Extraction

Information was extracted from scaled images using convolutional layers. The study's next phase will focus on feature extraction, fine-tuning the model before training, and applying CNN modelling to the development of a malaria disease detection system.

3.2.1 Transfer learning (TL)

The base network is trained using base datasets, after which the first-step features are applied to the other network's training on the dataset for malaria. The application of pre-train models on comparable data produced positive results for image classification tasks. Only a few businesses have produced models like the Microsoft ResNet, the Google Inception, and the Oxford VGG that need months to train using current hardware. These models are available for download, and they may be combined with more recent models that use images as input to get results that are more accurate. In order to identify malaria disease, the pre-trained VGG16 model will be trained on the malaria dataset.

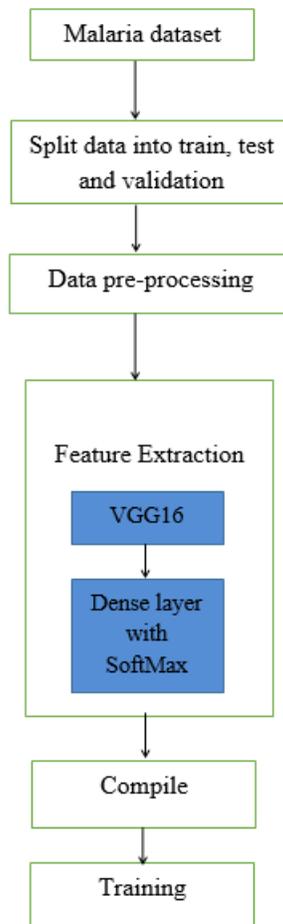


Figure 1. Deep learning model system overview

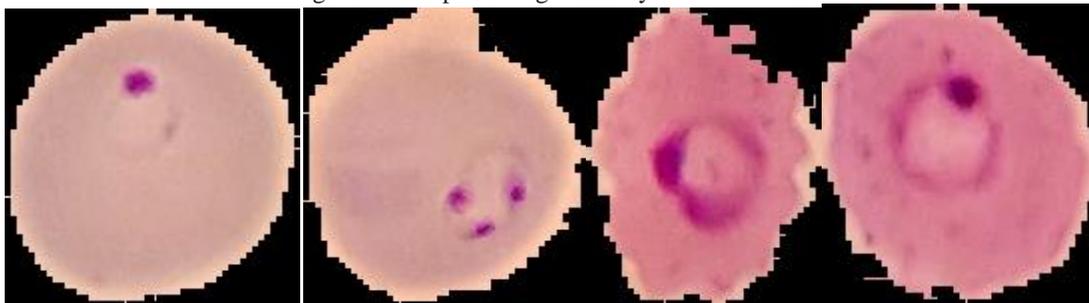


Figure 2: Infected malaria parasite blood smear sample images

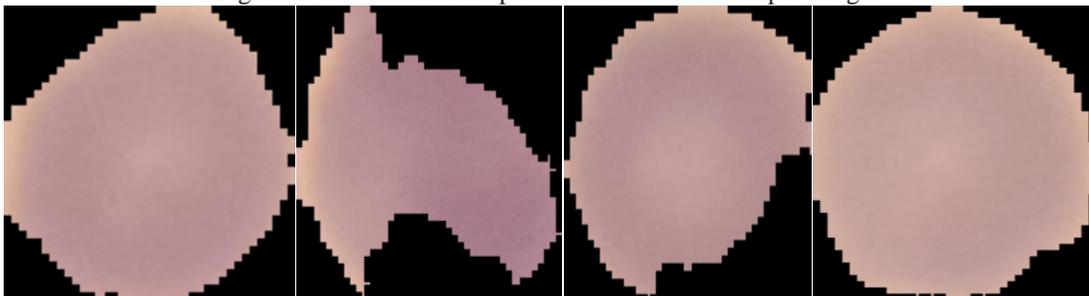


Figure 3: Uninfected blood smear sample images

3.2.2 VGG

At the 2014 "Image Net Large Scale Visual Recognition Challenge (ILSVRC)," VGG came in second in the image classification

test and first in the image localization test. Academics from Oxford built VGG and put the weights and structure online. Only 3*3 convolution layers, 2*2 maximum pooling layers, and completely connected layers at the end were used to generate the structure seen in Figure 6. The received image's dimensions should be 224*224*3. (RGB picture). The VGG16 model (figure 4) is being used to identify malarial infection.



Figure 4: VGG16 Architecture (Image source: [35])

4. Experiment results

The 224x224 pixel scaled blood smear photos in the malaria dataset include both parasite and uninfected blood smear images. 416 pictures were in the train and validation sets, while 134 pictures were in the test set. The model was trained utilising a free GPU in the experiment, which was carried out in Google Collab.

The photos will be input into a pre-trained VGG16 that includes imagenet pre-train weights, and the fully - connected dense layer with softmax activation will be the final layer. Pre-train weights will be used to learn the input data, and a single learning layer would be densely activated by the function softmax, which works well for category classification. Adam optimizer and Categorical crossentropy were utilised to determine loss during compilation. Additionally, the model were trained upto 100 epochs and batch size is 32. Accuracy (see equation 1) and loss were used to calculate model performance. Quantitative results achieved by the proposed system is 99 percent as train accuracy, 97 percent as validation accuracy, train loss 0.02, validation loss 0.1, and results is shown in figure 5. Our deep learning proposed model is able to correctly predict malaria parasite from blood smear images.

$$\text{Accuracy} = \frac{\text{True positive} + \text{True Negatives}}{\text{False Negative} + \text{True Negative} + \text{False positive} + \text{True Positive}} \quad (1)$$

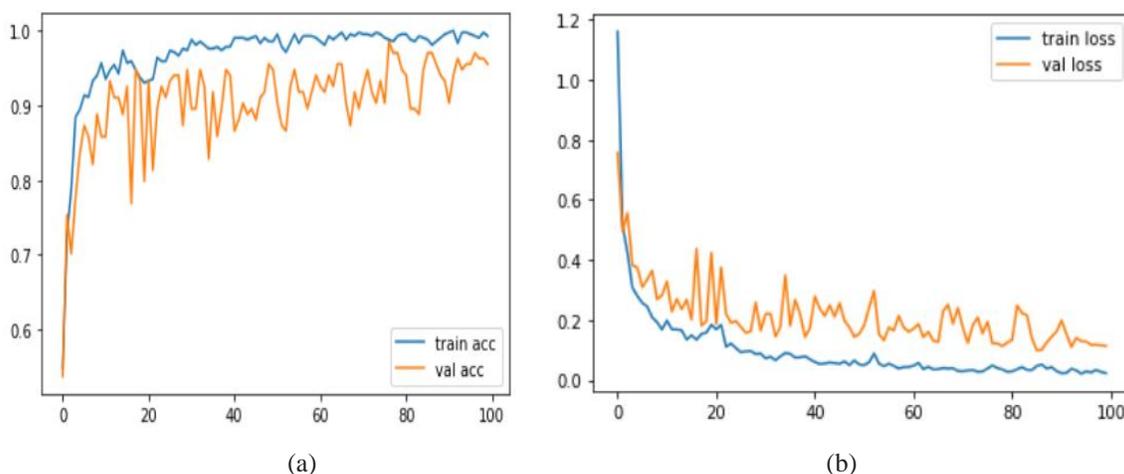


Figure 5. (a) validation and train accuracy graph (b) validation and train loss graph

5. Efficacy and safety of carcia papaya leaf extract on malaria

The papaya fruit comes from the Carica papaya plant, which was first cultivated in Southern Mexico and Central America but is now produced in most other regions of the world. When the fruit is mature, the skin turns from green to orange and the meat

turns from yellow to orange or red. Additionally, it has several bitter yet eatable black seeds. The enzyme papain, which is found in this fruit, aids in breaking down the complex protein chains found in muscles. It has been noted that the leaf extract is good for patients with dengue and malaria, respectively, and that it has potent antimalarial activities and increases platelet count.

The biological activity of *Carica papaya* plant extract has received a lot of interest, probably as a result of the large number of components, including the essential compounds chymopapain and papain, which is present in papaya. These substances together or separately to induce larvicidal action against *Anopheles stephensi* larvae.

5.1 Treatment with papaya leaf extract

The juice from the leaves of the *Carica papaya* plant, a member of the Caricaceae family, may aid people with malaria by raising their platelet counts. The extracts are predicted to have qualities that stabilize membranes and protect blood cells from stress-related cell death. The leaf extracts in this medicine may be helpful for people with malaria because they may prevent platelet lysis. Papaya leaf juice will ensure that your platelets and red blood cells grow. For the body's billions of cells to receive oxygen, red blood cells are necessary. The immune system could benefit from increased oxygen levels in the body, quickening the recovery from malaria. Papaya leaf juice can also aid in fever reduction.

5.1.1 Dosage and precautions

Any stage of the malaria disease might be treated with papaya leaf extract. However, it must be used from the first day of fever for optimal benefits. Until you have fully recovered from the sickness, papaya leaf extract can be given as syrup; For adults, give 30ml 3 times in day just before food. For children, give 5-10ml 3 times daily. It is suggested not to interrupt the course of the treatment. To get over the bitter taste, take a few sips of cool water very away after taking the papaya leaf extract. If you have a papaya allergy, avoid using papaya leaf extract.

5.1.2 Papaya leaf extract preparation and storage

- Grab ripe, fresh, healthy papaya leaves from a tree that bears fruit.
- Separate the main stem from the leaves before thoroughly washing them under running water.
- Put papaya leaves 50g into a mortar and pestle after weighing them.
- Include 25g of sugar and 50ml of boiled and chilled water.
- Pulp the aforementioned mixture well for 15 minutes.
- Mix this pulp thoroughly, then set aside for 30 minutes.
- Using your hands, squeeze the pulp to extract the juice.
- In the lowest section of the refrigerator (+4 oC), you may keep this recipe for 24 hours.
- Before taking the medication, shake the bottle thoroughly.

6. Conclusion

Proposed a technique for employing transfer learning, a deep learning approach, on a VGG16 model that has already been trained, to automatically identify the malaria parasite from microscopic pictures of blood smears. Dataset is divided into test set, which makes up 20% of the total, and train and validation sets, which make up 80%. Original photos are downsized to 224x224 before being given to the VGG16 deep model that has been previously trained. Quantitative findings include a train accuracy of 99 percent, a validation accuracy of 97 percent, a train loss of 0.02 and a validation loss of 0.1 for the proposed system. The malaria parasite can be accurately predicted from blood smear pictures using our deep learning-based approach. Papaya leaf extract can be used to treat malaria at any stage. Investigated the efficacy and safety of papaya leaf extract on malaria, as for best results, it must be taken starting on the first day of a fever, though. Papaya leaf extract can be taken as a syrup; for adults, take 30ml three times a day shortly before eating until recovery. Give youngsters 5 to 10 ml three times per day.

REFERENCES

- [1] <https://www.who.int/news-room/fact-sheets/detail/malaria#:~:text=In%202020%2C%20there%20were%20an,and%2096%25%20of%20malaria%20deaths.>
- [2] Rosado, Luís, et al. "A review of automatic malaria parasites detection and segmentation in microscopic images." *Anti-Infective Agents* 14.1 (2016): 11-22.
- [3] Razzak, Muhammad Imran, Saeeda Naz, and Ahmad Zaib. "Deep learning for medical image processing: Overview, challenges and the future."

Classification in BioApps (2018): 323-350.

- [4] Ross, Nicholas E., et al. "Automated image processing method for the diagnosis and classification of malaria on thin blood smears." *Medical and Biological Engineering and Computing* 44.5 (2006): 427-436.
- [5] Shen, Hongda, et al. "Lossless compression of curated erythrocyte images using deep autoencoders for malaria infection diagnosis." 2016 Picture coding symposium (PCS). IEEE, 2016.
- [6] Das, Dev Kumar, R. Mukherjee, and C. Chakraborty. "Computational microscopic imaging for malaria parasite detection: a systematic review." *Journal of microscopy* 260.1 (2015): 1-19.
- [7] Tek, F. Boray, Andrew G. Dempster, and Izzet Kale. "Parasite detection and identification for automated thin blood film malaria diagnosis." *Computer vision and image understanding* 114.1 (2010): 21-32.
- [8] Y. Zhang, Y. Qian, D. Wu, M. Shamim Hossain, A. Ghoneim, and M. Chen, "Emotion-aware multimedia Systems security," *IEEE Transactions on Multimedia*, vol. 21, no. 3, pp. 617–624, 2019.
- [9] Y. Zhang, X. Ma, J. Zhang, M. S. Hossain, G. Muhammad, and S. U. Amin, "Edge intelligence in the cognitive internet of things: improving sensitivity and interactivity," *IEEE Network*, vol. 33, no. 3, pp. 58–64, 2019.
- [10] X. Ma, R. Wang, Y. Zhang, C. Jiang, and H. Abbas, "A name disambiguation module for intelligent robotic consultant in industrial internet of things," *Mechanical Systems and Signal Processing*, vol. 136, article 106413, 2020.
- [11] Y. Zhang, M. S. Hossain, A. Ghoneim, and M. Guizani, "COCME: content-oriented caching on the mobile edge for wireless communications," *IEEE Wireless Communication*, vol. 26, no. 3, pp. 26–31, 2019.
- [12] J. Wang, Y. Miao, P. Zhou, M. S. Hossain, and S. M. M. Rahman, "A software defined network routing in wireless multihop network," *Journal of Network and Computer Applications*, vol. 85, pp. 76–83, 2017.
- [13] A. K. Sangaiah, D. V. Medhane, T. Han, M. S. Hossain, and G. Muhammad, "Enforcing position-based confidentiality with machine learning paradigm through mobile edge computing in real-time industrial informatics," *IEEE Transactions on Industrial Informatics*, vol. 15, no. 7, pp. 4189–4196, 2019.
- [14] M. A. Rahman, M. M. Rashid, M. Shamim Hossain, E. Hassanain, M. F. Alhamid, and M. Guizani, "Blockchain and IoT-Based Cognitive Edge Framework for Sharing Economy Services in a Smart City," *IEEE Access*, vol. 7, pp. 18611–18621, 2019.
- [15] M. F. Alhamid, M. Rawashdeh, H. Al Osman, M. S. Hossain, and A. El Saddik, "Towards context-sensitive collaborative media recommender system," *Multimedia Tools and Applications*, vol. 74, no. 24, pp. 11399–11428, 2015.
- [16] Y. Zhang, Y. Li, R. Wang, M. S. Hossain, and H. Lu, "Multi-Aspect Aware session-based recommendation for intelligent transportation services," *IEEE Transactions on Intelligent Transportation Systems*, pp. 1–10, 2020.
- [17] Y. Zhang, R. Wang, M. S. Hossain, M. F. Alhamid, and M. Guizani, "Heterogeneous information network-based content caching in the internet of vehicles," *IEEE Transactions on Vehicular Technology*, vol. 68, no. 10, pp. 10216–10226, 2019.
- [18] "This New App Helps Doctors Diagnose Malaria in Just 2 Minutes," <https://www.globalcitizen.org/en/content/appdiagnose-malaria-uganda>.
- [19] N. E. Ross, C. J. Pritchard, D.M. Rubin, and A. G. Dusé, "Automated image processing method for the diagnosis and classification of malaria on thin blood smears," *Medical & Biological Engineering & Computing*, vol. 44, no. 5, pp. 427–436, 2006.
- [20] D. K. Das, M. Ghosh, M. Pal, A. K. Maiti, and C. Chakraborty, "Machine learning approach for automated screening of malaria parasite using light microscopic images," *Micron*, vol. 45, pp. 97–106, 2013.
- [21] M. Poostchi, K. Silamut, R. J. Maude, S. Jaeger, and G. R. Thoma, "Image analysis and machine learning for detecting malaria," *Translational Research*, vol. 194, pp. 36–55, 2018.
- [22] M. S. Hossain, M. Al-Hammadi, and G. Muhammad, "Automatic fruit classification using deep learning for industrial applications," *IEEE Transactions on Industrial Informatics*, vol. 15, no. 2, pp. 1027–1034, 2019.
- [23] "MOMALA," <https://momala.org/malaria-diagnosis/>.
- [24] M. Usama, B. Ahmad, J. Wan, M. S. Hossain, M. F. Alhamid, and M. A. Hossain, "Deep feature learning for disease risk assessment based on convolutional neural network with intra-layer recurrent connection by using hospital big data," *IEEE Access*, vol. 6, pp. 67927–67939, 2018.
- [25] N. Srivastava, G. Hinton, A. Krizhevsky, I. Sutskever, and R. Salakhutdinov, "Dropout: a simple way to prevent neural networks from overfitting," *Journal of Machine Learning Research*, vol. 15, pp. 1929–1958, 2014.
- [26] M. Masud, M. S. Hossain, and A. Alamri, "Data interoperability and multimedia content management in e-health systems," *IEEE Transactions on Information Technology in Biomedicine*, vol. 16, no. 6, pp. 1015–1023, 2012.
- [27] O. B. Leal Neto, C. M. Albuquerque, J. O. Albuquerque, and C. S. Barbosa, "The schisto track: a system for gathering and monitoring epidemiological surveys by connecting geographical information systems in real time," *JMIR Mhealth Uhealth*, vol. 2, no. 1, article e10, 2014.
- [28] S. Kaewkamnerd, C. Uthaihibull, A. Intarapanich, M. Pannarut, S. Chaotheing, and S. Tongshima, "An automatic device for detection and classification of malaria parasite species in thick blood film," *BMC Bioinformatics*, vol. 13, Supplement 17, p. S18, 2012.
- [29] D. Anggraini, A. S. Nugroho, C. Pratama, I. E. Rozi, A. A. Iskandar, and R. N. Hartono, "Automated status identification of microscopic images obtained from malaria thin blood smears," in *Proceedings of the 2011 International Conference on Electrical Engineering and Informatics*, Bandung, Indonesia, July 2011.
- [30] S. Rajaraman, S. K. Antani, M. Poostchi et al., "Pre-trained convolutional neural networks as feature extractors toward improved malaria parasite detection in thin blood smear images," *PeerJ*, vol. 6, article e4568, 2018.
- [31] G. P. Gopakumar, M. Swetha, G. S. Siva, and G. R. K. Sai Subrahmanyam, "Convolutional neural network-based malaria diagnosis from focus stack of blood smear images acquired using custom-built slide scanner," *Journal of Biophotonics*, vol. 11, no. 3, 2018.
- [32] Z. Liang, A. Powell, I. Ersoy et al., "CNN-based image analysis for malaria diagnosis," in *2016 IEEE International Conference on Bioinformatics and Biomedicine (BIBM)*, pp. 493–496, Shenzhen, China, December 2016.
- [33] Rajaraman S, Jaeger S, Antani SK., "Performance evaluation of deep neural ensembles toward malaria parasite detection in thin-blood smear images," *PeerJ* 7:e6977 2019 <https://doi.org/10.7717/peerj.6977>
- [34] Rajaraman S, Antani SK, Poostchi M, Silamut K, Hossain MA, Maude RJ, Jaeger S, Thoma GR. 2018. Pre-trained convolutional neural networks as feature extractors toward improved malaria parasite detection in thin blood smear images. *PeerJ* 6:e4568 <https://doi.org/10.7717/peerj.4568>
- [35] <https://www.geeksforgeeks.org/vgg-16-cnn-model/>
- [36] Sreedhar, B., Manjunath Swamy BE, and M. Sunil Kumar. "A comparative study of melanoma skin cancer detection in traditional and current image processing techniques." 2020 Fourth International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud)(I-SMAC). IEEE, 2020.
- [37] Balaji, K., P. Sai Kiran, and M. Sunil Kumar. "Resource aware virtual machine placement in IaaS cloud using bio-inspired firefly algorithm." *Journal of Green Engineering* 10 (2020): 9315-9327.
- [38] Natarajan, V. A., Kumar, M. S., Patan, R., Kallam, S., & Mohamed, M. Y. N. (2020, September). Segmentation of nuclei in histopathology images using fully convolutional deep neural architecture. In *2020 International Conference on computing and information technology (ICIT-1441)* (pp. 1-7). IEEE.
- [39] Kumar, M. S., & Prakash, K. J. (2019). Internet of things: IETF protocols, algorithms and applications. *Int. J. Innov. Technol. Explor. Eng.* 8(11), 2853-

- [40] Davanam, G., Kumar, T. P., & Kumar, M. S. (2021). Efficient energy management for reducing cross layer attacks in cognitive radio networks. *Journal of Green Engineering*, 11, 1412-1426.
- [41] S. Shiva Prakash, "Educating and communicating with deaf learner's using CNN based Sign Language Prediction System", *International Journal of Early Childhood Special Education*, Vol 14, Issue 02, 2022.
- [42] Prasad, P. Y., Prasad, D., Mallewari, D. N., Shetty, M. N., & Gupta, N. Implementation of Machine Learning Based Google Teachable Machine in Early Childhood Education. *International Journal of Early Childhood*, 14(03), 2022.
- [43] Kumar, M. S., Ganesh, D., Turukmane, A. V., Batta, U., & Sayyadliyakat, K. K. (2022). Deep Convolution Neural Network Based solution for Detecting Plant Diseases. *Journal of Pharmaceutical Negative Results*, 464-471.
- [44] Natarajan, V. A., Tamizhazhagan, V., Tangudu, N., & Kumar, M. S. (2022). Analysis of Groundwater Level Fluctuations and its Association with Rainfall Using Statistical Methods. *JOURNAL OF ALGEBRAIC STATISTICS*, 13(3), 1895-1904.
- [45] Kumar, M. S., Harika, A., Sushama, C., & Neelima, P. (2022). Automated Extraction of Non-Functional Requirements From Text Files: A Supervised Learning Approach. *Handbook of Intelligent Computing and Optimization for Sustainable Development*, 149-170.