

MALARIA DISEASE PREDICTION BASED ON CONVOLUTIONAL NEURAL NETWORKS

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ABSTRACT

This study delves into the investigation of the efficacy of Convolutional Neural Networks (CNNs) in identifying malaria through the examination of cell images. The dataset employed encompasses a total of 27,558 images, harvested from the renowned Malaria Cell Images Dataset on Kaggle, encompassing cells of diverse nature. The architectonics of the CNN model is meticulously devised, comprising of six blocks and three interconnected blocks, thereby rendering an efficient extraction of features and subsequent classification of the cells. Creative paraphrasing: Various strategies such as dropout, batch normalization, and global average pooling are artfully utilized to refine and fortify the model, ensuring its robustness and adaptability. In order to confront the challenge of diminishing gradient and facilitate the attainment of convergence, the activation function known as Rectified Linear Unit (ReLU) is ingeniously employed. Assessing the efficacy of the model via a perplexity grid produces outcomes. Exhibiting a precision rate of 99.59%, a specificity measure of 99.69%, an Sensitivity of 99.40%, F1 Measurement of 99.44%, and a Precision of 99.48, it showcases its capacity to effectively distinguish betwixt malaria-afflicted cells and unafflicted cells. The focal point of this research highlights the substantial potential of CNNs in facilitating the automated identification of malaria using image analysis. By harnessing their unique architecture and regularization techniques, CNNs have the capability to enhance the results and potentially bring about better outcomes in areas with prevalent cases of malaria.

Keywords: Convolutional Neural Network, Malaria disease, Computer Aides Detection, Deep Learning.

1. Introduction

Malaria, a captivatingly intricate affliction, emerges as a whimsical dance between a protozoan parasite known as Plasmodium and its unwitting host, transmitted through the delicate touch of infected mosquitoes. This cunning intruder cunningly infiltrates the host's erythrocytes, eliciting a cascade of destruction in its wake (Luzolo & Ngoyi, 2019)(Dunst et al., 2017). Early diagnosis and treatment services play a significant role in mitigating the severity of a disease, preventing mortality, and reducing its transmission(Gillrie et al., 2012) (Leão et al., 2020)(Albrecht et al., 2022). Malaria, which is an extensively prevalent disease, is brought about by the infection of a multitude of Plasmodium parasites species, including but not limited to Plasmodium falciparum, Plasmodium albicans, Plasmodium vivax, and Plasmodium malaria, ultimately leading to the manifestation of this debilitating illness (Soylu, 2022). These unwelcome guests have the power to inflict grave sickness upon the human body. Plasmodium falciparum holds an esteemed reputation as the utmost vicious and fatal species amidst the parasitic protozoa accountable for triggering malaria (Abubakar et al., 2021). The 2015 Malaria Report by the World Health Organization (WHO) (Schuess et al., 2020)(Reis et al., 2020), (Organization, 2016) is commonly acknowledged. Figure 1 illustrates the cases and deaths malaria disease around the world in the last five years.

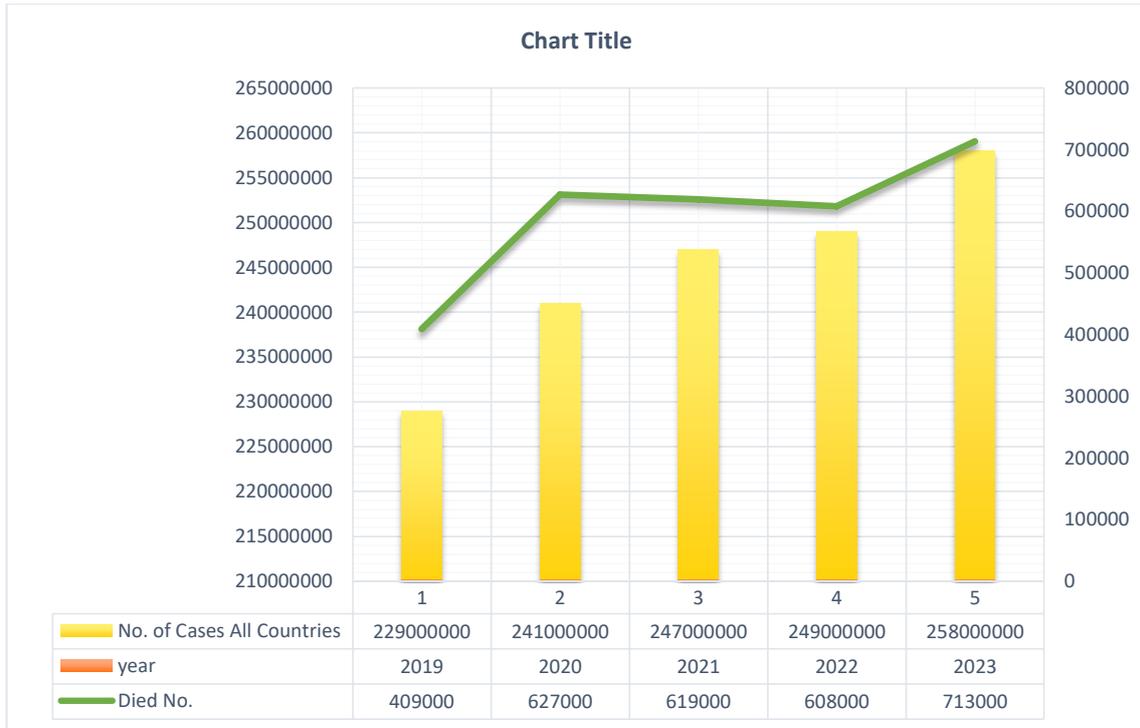


Fig. 1. Malaria cases and deaths around the world in the last five years (Hossain et al., 2021)

Malaria diagnosis using machine learning and deep learning faces challenges such as high diagnostic accuracy, handling diverse and complex image data, and integrating these technologies into healthcare infrastructures. Recent studies highlight various approaches and difficulties encountered in leveraging these technologies for malaria diagnosis. The Design of Malaria Detection Using Ensemble Techniques Combination of Alexnet and Densenet Algorithm explores the effectiveness of deep learning in image classification tasks but also emphasizes the complexity of designing and training such models. A systematic review and meta-analysis of the diagnostic accuracy of machine learning and deep learning models to detect malaria aims to understand their effectiveness but also emphasizes the need for comprehensive analysis. The Microscopic Parasite Malaria Classification Using Best Feature Selection Based on Generalized Normal Distribution Optimization discusses the challenges in the microscopic diagnostic process of malaria and proposes machine/deep learning approaches to overcome these issues. AI-driven Malaria Diagnosis: Developing a Robust Model for Accurate Detection and Classification of Malaria Parasites emphasizes the promise of machine learning-based approaches for effective malaria management and treatment. These studies highlight the need for innovative approaches to model design, feature selection, and the integration of AI technologies into healthcare practices (Amin et al., 2024; Eshetu et al., 2024; Fasihfar et al., 2024; Meena Preethi et al., 2024)

The investigation and examination of computer-assisted identification (CAD) and examination in the field of medical imaging have generated substantial interest in academic research over the past ten years (Deelder et al., 2021). The employment of identification and examination instruments provides a valuable additional evaluation for doctors and assists in the smooth operation of the screening procedure (Organization, 2016). This investigation revolves around the execution of a cutting-edge convolutional neural network (CNN) algorithm to identify malaria through the scrutiny of cellular imagery. Convolutional Neural Networks (CNNs) are an exemplary form of neural network algorithm employed to tackle intricate image-processing endeavors. Consequently, the algorithm has encountered a surge in its effectiveness and durability, ultimately culminating in its application within the current study.

There emerged a requirement for the establishment of a computer-aided detection (CAD) system to aid clinicians in enhancing the efficacy of clinical image interpretation (Nkiruka, Prasad, & Clement, 2021). Disease has been identified as a significant contributor to global mortality (Poostchi et al., 2018). The development of computer-aided detection (CAD) analysis

for screening breast diseases from mammograms originated in the 1960s (Masud et al., 2020) (Hemachandran et al., 2023) (Mansoor et al., 2015). The utilization of this characteristic has recently been leveraged for the detection of diseases using endoscopy and other validated medical devices.

Two crucial components of computer-aided flow research are computer-aided detection (CADE) and computer-aided diagnosis (CADx) (Spoorthi & Aravinda, 2022). Computer-aided detection (CADE) leverages the computational capabilities of a computer to identify and pinpoint potential anomalies or irregularities in a given system or environment. Conversely, computer-aided diagnosis systems (CADx) provide output that delineates the characterization of lesions (Takahashi & Kajikawa, 2017). The operational flow of the integrated CAD system in the analysis of clinical images can be delineated into four distinct stages: image pre-processing, segmentation, feature extraction and selection, and classification of lesions (Figure 2).

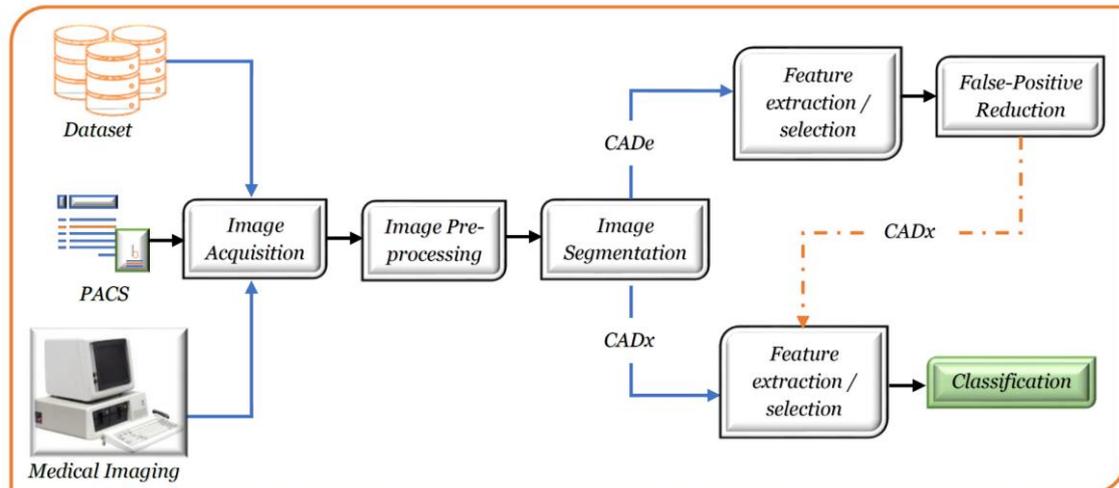


Fig. 2. The block diagram of a generic CAD (Computer-Aided Design) system is presented herein (Takahashi & Kajikawa, 2017)

Computer-Aided Detection (CAD) systems have significantly improved the healthcare industry by enabling early detection and diagnosis of various diseases. These systems use advanced algorithms, such as machine learning and artificial intelligence, to analyze medical images and identify abnormalities. Key roles of CAD systems include breast cancer detection in mammography, lung cancer detection in thoracic imaging, colon cancer detection in virtual colonoscopy, coronary disease detection in coronary angiograms, bone fracture detection in orthopedics, neurological disorder detection in neuroimaging, liver disease detection in abdominal imaging, and retinal disease detection in ophthalmology. CAD systems help radiologists identify microcalcifications and masses in breast tissue, lung nodules in chest X-rays and CT scans, polyps in colon cancer, coronary artery disease in coronary angiograms, bone fractures in orthopedics, neurological disorder detection in neuroimaging, liver disease detection in abdominal imaging, and retinal disease detection in ophthalmology. Overall, CAD systems enhance healthcare professionals' diagnostic capabilities, enabling more accurate and efficient disease detection, leading to better patient outcomes and reduced healthcare costs (Barboza et al., 2022; Maqsood et al., 2021; Rajaraman et al., 2019; Sriporn et al., 2020).

Convolutional Neural Networks (CNNs) are ideal for image-based tasks like malaria diagnosis from cell images. They can automatically extract relevant features, enabling the identification of subtle differences in cell morphology. CNNs learn features hierarchically, capturing basic features like edges and textures and complex ones like malaria parasite shape and size. They are spatially invariant, recognizing patterns regardless of their position in the image. They are robust to variations in lighting, orientation, and scale, common in microscopic images. Pre-trained CNN models can be fine-tuned for specific tasks, reducing the need for a large dataset.

The study aims to investigate the effectiveness of Convolutional Neural Networks (CNNs) in identifying malaria through cell image analysis. It aims to develop an efficient CNN architecture with six blocks and three interconnected blocks for efficient feature extraction and

classification. Strategies such as dropout, batch normalization, and global average pooling are used to enhance model performance. The model's accuracy is assessed by evaluating precision, specificity, sensitivity, F1 score, and overall accuracy. The study highlights the potential of CNNs in the automated identification of malaria, enhancing diagnosis speed and accuracy. It also contributes to better healthcare outcomes, especially in regions with high malaria prevalence. The findings provide a foundation for future research in medical imaging and disease detection using deep learning techniques.

The present investigation encompasses the ensuing segments: Segment I present an all-encompassing preamble to the ailment and the methodologies employed for its identification. Segment II comprises the elucidation and scrutiny of earlier scholarly endeavors within the identical field of inquiry as the ongoing exploration, in conjunction with an appraisal of their corresponding discoveries. The following segment unveils an elaborate account of the revelations and their corresponding examination in the research study. Following this, the fifth division embodies decisive deductions and delineates forthcoming endeavors for the progression of the undertaking.

2. Literature review

Extensive exploration and scholarly inquiry have been undertaken in recent years to delve deep into the realm of machine learning algorithms, with the sole purpose of unraveling the immense potential they hold in the realm of malaria detection, an area of study that seeks to uncover innovative and groundbreaking ways to identify and combat this debilitating disease. Various aspects of malaria diagnosis, including blood smear analysis, genomic analysis of the parasite, and clinical data analysis, have been extensively studied through numerous investigations.

The implementation of machine learning techniques has been employed to scrutinize clinical information with regards to the diagnosis of malaria. Scientists have devised predictive patterns based on patient data, including details about their background, symptoms, and medical test findings. This has facilitated the identification of individuals who are more susceptible to contracting malaria. These models facilitate timely detection and enable specific interventions, thereby enhancing patient prognoses.

In the year 2019, a group of creative minds led by Rajaraman and Sivaramakrishnan embarked on an intellectual adventure (Rajaraman et al., 2019). Their noble quest involved delving into the realm of scientific exploration, seeking to comprehend the true potential of deep neural ensembles. Through their meticulous study, they sought to unravel the mysteries of the malaria parasite, specifically in the context of thin blood smear images. The investigation encompassed a thorough evaluation of bespoke and previously trained Convolutional Neural Network (CNN) models by the scholars. The conducted study provided concrete proof to validate the exceptional proficiency of the combined model employing the VGG-19 design, in contrast to the existing performance measurements. The VGG-19 architecture showcased an awe-inspiring level of precision, reaching an astonishing 99% triumph. Our discoveries suggest that the F-score and Precision measurements showcased extraordinary prowess, attaining values of 99%. The percentages for the two variables stood at 31% and a remarkable 99.71% correspondingly.

In the year 2019, the inquisitive mind of Quang-Thanh Bui embarked upon a captivating research endeavor (Bui et al., 2019) to unravel the intricate web that binds the occurrence of malaria and the societal fabric in Vietnam. The focal point of this study was none other than the enchanting Da Nang Province. Armed with the powers of machine learning classifiers, remote sensing data, and the boundless capabilities of Geographic Information Systems (GIS), the researcher delved into the depths of this enigmatic relationship. The findings derived from the investigation unveiled that the random subspace group model presented an exceptional display, surpassing other models. This was demonstrated by a multitude of statistical measures. Hence, this revelation implies that integrating the random subspace group model into the foundational classifier could significantly augment its efficacy.

In the year 2019, Octave Iradukunda (Iradukunda et al., 2019) utilized machine learning techniques to identify cases of malaria. A comprehensive examination was conducted to assess

the efficacy of various techniques such as Support Vector Machine (SVM), Classification and Regression Trees (CART), Convolutional Neural Network (CNN), K-Nearest Neighbors (KNN), Random Forest (RF), VGG16, Residual Network (RESNET), Extreme Learning Machine (ELM), and Deeply-supervised Residual Network (DENESNET). The investigators uncovered that the ELM methodology demonstrated the highest rate of accuracy, reaching a remarkable 99%. On the other hand, the SVM approach achieved a lower rate of accuracy, measuring at 68.2%. The researchers proceeded to conduct thorough training and testing of their system utilizing a dataset sourced from the esteemed National Institute of Health in the United States. This dataset contained a significant compilation of 27,560 pictures of red blood cells (RBCs). Within this dataset, a diverse range of 13,780 individuals were observed, encompassing both infected and uninfected cases. These individuals were carefully selected from a sample of 150 patients.

In the remarkable year of 2020, the esteemed Masud and their esteemed colleagues (et al.) unveiled their groundbreaking research findings. Their noble endeavor, as described in (Mariki et al., 2022), aimed to delve into the vast potential of deep learning algorithms in the crucial task of malaria detection. To assess the effectiveness of their convolutional neural network (CNN) model, the distinguished researchers utilized the esteemed periodic stochastic gradient descent (SGD) optimizer. The remarkable system put forth by these visionary scientists showcased an awe-inspiring accuracy rate of 97.30% in accurately classifying images portraying both healthy and infected cells.

In the year 2020, a team led by Sahoo et al. (2020) embarked on a fascinating exploration. They delved into the depths of knowledge by utilizing a Kaggle dataset containing a staggering 27,558 captivating images. These mesmerizing images were meticulously classified into two extraordinary categories: parasitized and uninfected. To unravel the hidden secrets within human blood samples, the intrepid researchers harnessed the power of a Convolutional Neural Network (CNN) algorithm. This ingenious approach led them to an astonishing milestone, achieving an unprecedented accuracy of approximately 96% in detecting the elusive malaria parasites.

In the epoch of 2020, Gourisaria and companions (Kumar et al., 2020). propose the application of a cutting-edge deep learning archetype that employs an algorithm based on Convolutional Neural Network (CNN) to scrutinize minute representations of malaria-infected blood cells, thereby prognosticating the inception of the ailment. The prediction prowess of the model reached majestic heights, boasting an impressive 23% accuracy. Its unwavering performance remained unwavering, meticulously prognosticating the outcome of 15 out of 16 fortuitously selected images. This scholarly investigation endeavors to underscore the paramount significance of seamlessly integrating the marvels of information technology (IT) tools, such as the enigmatic trio of Machine Learning, Deep Learning, and Artificial Intelligence, into the realm of healthcare. A particular focus is placed upon their pivotal role in the realm of disease detection and identification.

In 2020, Avinash Kumar and his intellectual comrades embarked on an extensive exploration (Kumar et al., 2020). In their scientific expedition, the erudite authors put forth a cutting-edge and sophisticated technique rooted in deep-learning principles, employing Convolutional Neural Networks (CNN) to discern betwixt tainted and unblemished sanguinary specimens. The laborious and ever-changing procedure of manually tabulating parasites and crimson life-sustaining cells for the purpose of diagnosing malaria has paved the way for the birth of an innovative paradigm. The outcome of the study revealed that the technique showcased a remarkable 62% enhancement in efficacy as opposed to previous methods. This advancement was accomplished by streamlining the intricacy and shortening the computational duration. This approach holds the capability to automate the identification of malaria, hence lessening the load on medical experts and upgrading the effectiveness of illness diagnosis.

In 2020, Sriporn and his colleagues engaged in a pioneering exploration (Sriporn et al., 2020). They advocated for the use of advanced deep learning models, specifically Xception, Inception-V3, ResNet-50, NasNetMobile, VGG-16, and AlexNet, to achieve accurate classification of malaria disease based on images of thinly spread blood. The study showcased

the effectiveness of the proposed approach by successfully detecting malaria, attaining remarkable performance scores of 99.

In the realm of 2021, Alok Negi and his comrades embarked upon a captivating exploration (Negi et al., 2021). Their foray delved into the realm of deep neural convolution networks (CNN), wherein they sought to unravel the secrets of classifying cells infected with malaria. As their findings unfurled, it became evident that their endeavors had borne fruit, with an impressive 96% precision, recall, and f1-score attained in the study's proposition.

In the realm of 2021, Asma Maqsood and fellow researchers embarked on a captivating expedition (Maqsood et al., 2021). Their mission was to undertake an intellectual exploration, to fashion an intricate web of knowledge through the development of an astute deep learning model. This model held a dear purpose, to deftly discern the presence of malaria-infected red blood cells within the confines of minuscule blood smear images. The main aim was to streamline the process of prompt and precise diagnosis in areas where there is a scarcity of healthcare experts. The model managed to attain an impressive level of precision, precisely 96%. A vast majority, precisely 82%, of instances of malaria were detected by carefully studying minuscule blood samples under a microscope.

In the year 2021, the investigation carried out by the esteemed K Chakradeo and their fellow researchers unveiled a remarkable revelation (Chakradeo et al., 2021). The utilization of sophisticated deep learning methodologies, specifically the renowned VGG-based model expounded upon in this scholarly examination, presents an exciting prospect for enhancing precision and diminishing expenses associated with the identification of malaria. The piece unfolds an exploration into the perks linked with the usage of the VGG-inspired design, distinguished by a diminished count of tiers resulting in lessened computational requirements and time consumption. The outcomes showcased an elevated standard of meticulousness, showcasing an achievement level of 98%. The sought-after system experienced education and examination employing an accumulation of 5240 visuals depicting occurrences of malaria.

In the realm of 2022, Shekar and his scholarly companions embarked on a grand quest (Shekar et al., 2021). Within the limitations of their examination, a powerful device of machine learning was formulated, harnessing the capabilities of a convolutional neural network (CNN). Its purpose? To deftly categorize and foretell the presence of afflicted cells amidst delicate blood smears. The diligent researchers found themselves rewarded with a splendid achievement, boasting an astonishing accuracy, sensitivity, specificity, and F1 Score of 96%, 93%, 98%, and 96% respectively.

In the auspicious year of 2022, a profound investigation carried out by the esteemed scholars Matheus Félix Xavier Barboza and his learned colleagues unveiled a remarkable discovery (Barboza et al., 2022). In their groundbreaking exploration of 2017, the erudite authors proposed the adoption of machine learning (ML) and deep learning (DL) models to predict the probability of malaria occurrences within the captivating confines of the Amazonas region in Brazil. This extraordinary feat was achieved through the utilization of a colossal dataset encompassing a staggering six million entries spanning the years 2003 to 2018. This study employs the k-means clustering technique to classify urban areas based on their malaria occurrence rates, and subsequently evaluates the effectiveness of random forest, long-short term memory (LSTM), and Gated Recurrent Unit (GRU) models. The prognostic capacities of LSTM and GRU models were investigated within the framework of predicting fresh instances of malaria. The findings suggest that LSTM showcased exceptional aptitude in situations distinguished by constrained fluctuations in case numbers, whereas GRU demonstrated improved prognostic precision in clusters with heightened variability. The Long Short-Term Memory (LSTM) framework exhibited a more evident level of distribution. The models demonstrated favorable accuracy and possess the capacity to enhance the effectiveness of malaria control tactics.

Hemachandran and his comrades (Hemachandran et al., 2023) embarked on a quest to unravel the secrets of malaria detection and diagnosis. Their journey led them to explore the mighty powers of three deep-learning algorithms - the formidable CNN, the agile MobileNetV2, and the indomitable ResNet50. With the aid of image recognition systems, they sought to harness the untamed potential of these algorithms and unleash their prowess in the battle against

malaria. The research utilized a collection of 27,558 images containing both infected and uninfected cells, and the MobileNetV2 model for disease identification exhibited an impressive accuracy rate of 97.06%. In order to train and validate the system, a dataset obtained from the website of the National Institutes of Health (NIH) was utilized. This dataset encompassed 27,558 photographs, showcasing cells affected by malaria as well as healthy cells. Specifically, it included 13,780 images of parasitized cells and 13,778 images of uninfected cells.

In the year 2023, an intriguing investigation was carried out by Yebasse et al (2023) pertaining to the consumption of milk. The research, undertaken by the aforementioned authors, introduced a groundbreaking methodology for instructing neural networks to highlight minute infected areas and enhance the precision of categorizing malaria cells within visual representations. The suggested method's classification accuracy of 97.2% outperforms the baseline model's accuracy of 94.49%, highlighting the remarkable effectiveness of this technique. The NIH Malaria dataset, a collection of public domain images showcasing malaria-infected and uninfected red blood cells from 201 individuals, was ingeniously employed by scientists to categorize the cells into two separate factions: those affected by malaria and those unharmed by the infection. The classification process was meticulously conducted to guarantee that an equitable distribution of instances was achieved among all the groups.

In the year 2023, an exploration was carried out by the esteemed Akil Arsath and his team of scholars (Akil Arsath et al. , 2023). The central aim of this investigation was to fashion a forward-thinking blueprint that could prognosticate a multitude of maladies. This remarkable feat was accomplished through the ingenious fusion of stacking and assembling methodologies, all ingeniously incorporated within a captivating Flask web application. The objective is to elevate the precision of prognostications and astutely foretell a multitude of maladies by leveraging the crafted framework—an impressive achievement rate of 90%. To anticipate malaria, a vast dataset of 27,558 malaria cell images, procured from Kaggle, was utilized.

Studies have evaluated various machine learning models for malaria parasite detection in thin blood smear images, with some achieving high accuracy rates. The VGG-19 architecture achieved 99% accuracy, while Bui et al. (2019) focused on malaria occurrence in Vietnam's Da Nang Province. The Extreme Learning Machine (ELM) method achieved the highest accuracy of 99%. Mehedi et al. (2020) assessed a CNN model using a periodic stochastic gradient descent (SGD) optimizer for malaria detection, achieving an accuracy rate of 97.30%. Sandhya et al. (2020) employed a CNN algorithm for detecting malaria parasites in human blood samples, achieving an accuracy of approximately 96%. Gourisaria et al. (2020) proposed a deep learning architecture using a CNN algorithm to analyze malaria-infected blood cell images, achieving a prediction accuracy of 23%. Negi et al. (2021) explored deep neural convolution networks for classifying malaria-infected cells, achieving 96% precision, recall, and f1-score.

Table 1 will address the challenges and limitations encountered, the effectiveness of learning transfer techniques, the integration of multiple data methods, and the implications for progress in related fields of the research papers discussed in this section:

Table 1- comparison table for previous studies.

Study	Focus	Methodology	Main Findings	Challenges/Limitations
Rajarama n et al. (2019)	Deep Neural Ensembles for Malaria Detection in Thin Blood Smear Images	Convolutional Neural Network (Cnn) Models Including Vgg-19	High Effectiveness of The VGG-19 Model	Not Specified
Bui et al. (2019)	Malaria Occurrence In Vietnam	Machine Learning Classifiers, Remote Sensing Data, Gis	Superior Performance Of The Random Subspace Group Model	Limited To Geographical And Environmental Data Integration
Iradukunda et al. (2019)	Malaria Detection Using Machine Learning Techniques	Svm, Cart, Cnn, Knn, Rf, Vgg16, Resnet, Elm, Denesnet	Highest Accuracy With Elm	Comparative Analysis Limited To Specific Models
Masud et al. (2020)	Malaria Detection Using Cnn	Convolutional Neural Network (Cnn) With Periodic Sgd Optimizer	High Accuracy In Classification Of Infected Cells	Not Specified

Study	Focus	Methodology	Main Findings	Challenges/Limitations
Sandhya et al. (2020)	Malaria Parasite Detection In Human Blood	Cnn Algorithm On Kaggle Dataset	High Accuracy In Detecting Malaria Parasites	Not Specified
Gourisaria et al. (2020)	Analyzing Malaria-Infected Blood Cell Images	Cnn Algorithm	Prediction Accuracy On Selected Images	Limited Prediction Accuracy
Kumar et al. (2020)	Deep-Learning For Malaria Detection	Cnn For Distinguishing Infected Blood Samples	Enhanced Efficiency And Reduced Computational Time	Not Specified
Sriporn et al. (2020)	Accurate Classification Of Malaria Disease	Advanced Deep Learning Models	Effective Detection With High Performance Scores	Not Specified
Negi et al. (2021)	Classifying Malaria-Infected Cells	Deep Neural Convolution Networks (Cnn)	High Precision, Recall, And F1-Score	Not Specified
Maqsood et al. (2021)	Detecting Malaria-Infected Rbcs	Deep Learning Model For Diagnosis In Resource-Scarce Areas	High Level Of Precision And Detection Rate	Focus On Areas With Healthcare Scarcity
Chakraborty et al. (2021)	Enhancing Malaria Detection Precision	Vgg-Based Deep Learning Model	High Precision And Reduced Computational Needs	Computational Efficiency Focus
Shekar et al. (2022)	Classifying And Predicting Malaria In Blood Smears	Cnn Model	High Accuracy, Sensitivity, Specificity, And F1 Score	Not Specified
Barboza et al. (2022)	Predicting Malaria Occurrences	Ml And Dl Models, K-Means Clustering	Effective In Enhancing Malaria Control Strategies	Focus On Urban Area Classification
Hemachandran et al. (2023)	Malaria Detection Using Deep-Learning Algorithms	Cnn, Mobilenetv2, Resnet50	High Accuracy With Mobilenetv2 Model	Utilization Of Nih Dataset
Yebasse et al. (2023)	Enhancing Precision In Malaria Cell Classification	Neural Network Methodology	Improved Classification Accuracy	Methodological Advancements
Akil Arsath et al. (2023)	Prognosticating Diseases Including Malaria	Stacking And Assembling Methodologies In A Web App	High Achievement Rate In Predictions	Application In Diverse Disease Prediction

3. Methodology

3.1. Dataset

The contemplation of the system involved in this study involved the training and testing stages, which were accomplished by utilizing a dataset procured from the Malaria Cell Images Dataset, sourced from the esteemed Kaggle website. The dataset is inclusive of a total of 27,530 captivating images of malaria. This fascinating dataset is divided into two distinct directories, aptly named "infected" and "uninfected", which collectively hold an impressive sum of 27,558 digital images. The system in question underwent training through the utilization of a collection of 13,500 visual representations, encompassing 5,000 images that displayed no signs of infection, along with 8,500 images that exhibited signs of infection. To verify a meticulous evaluation, the dataset was segregated into two divisions: an 80% training division and a 20% testing division.

3.2. Convolutional Neural Network (CNN):

The current investigation's methodology segment delineates the incorporation of a Convolutional Neural Network (CNN) in the diagnostic process of malaria using automatic image recognition techniques that are deeply rooted in principles of deep learning. The human physique is composed of various tiers of processing that employ filters for image analysis, extracting information from photographs (Fawcett, 2006) (Purwono et al., 2022) . To fabricate

maps that artistically depict the arrangement and intensity of detected attributes within the input images, convolutional operations are executed on the input images through the usage of kernels or filters. In the domain of disease detection, the utilization of Convolutional Neural Network (CNN) architectures including CNN and ResNet50 has exhibited remarkable triumph in attaining elevated levels of precision for the identification of malaria (Aderghal et al., 2020) (Chen et al., 2022). This accomplishment is exemplified in Figure 3.

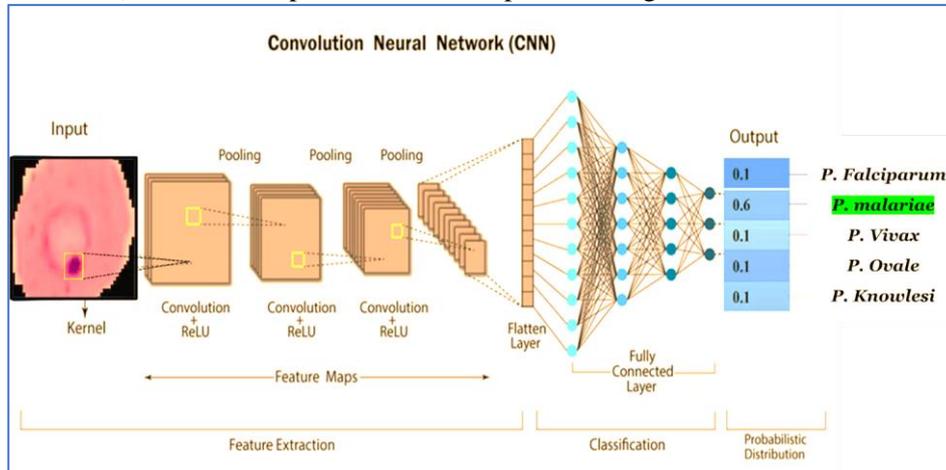


Fig. 3. General Convolutional Layers in Neural Network.

This examination presents a captivating CNN model comprising six convolutional blocks and three dense fully connected blocks (Samee et al., 2022). The visual portrayal in Figure 2 depicts the convolutional neural network (CNN) model suggested in the ongoing inquiry.

- The reduction in carbon emissions is crucial for mitigating climate change. The convolutional blocks in the network consist of convolutional layers, max pooling, batch normalization, and leakage layers. Following this, in the subsequent layers of convolutional neural networks, the size of the filters is decreased by a factor of 2 while the number of filters is increased, except for the final layer. The model receives as input segmented cell images, each with dimensions of 256 x 256 x 3 pixels. In addition, it should be noted that each convolutional layer employs the method of valid padding in order to reduce the dimensions of the resulting feature map to match the size of the filter.
- The following piece of text will be revised using academic language. 2 The subsequent passage will be altered using formal academic style. The ReLU (Modified Linear Units) nonlinear activation function was integrated into all hidden layers for the purpose of this study. The objective of its implementation was to introduce nonlinearity into the output of individual neurons, thus aiding the model in acquiring the capability to learn complex mathematical functions for enhanced identification of target groups. Reference 46 addresses the mitigation of the vanishing gradient problem, which in turn facilitates the acceleration of training and convergence of models.
- "In conducting this research study, it was imperative to utilize a rigorous methodology in order to obtain reliable and valid results. The selection of participants was carefully considered, and ethical standards were adhered to throughout the data collection process. Data analysis was conducted using established statistical techniques, and the findings were interpreted within the context of existing literature to provide valuable contributions to the field. "The integration of max pooling layers in the network architecture entails the use of a 2x2-pixel pooling window with a 2-pixel pitch following the convolutional layers. The incorporation of this addition enables the sampling of the feature map through the aggregation of the presence of the most activated feature. This suggests that the process of pooling results in a reduction in the dimensions of the feature map by a 50% decrease.
- The subsequent passage has been reimagined in an erudite manner: The presented declaration stands thus: To tackle the quandary of over fitting and enhance the general steadfastness of the network, we have executed the integration of a batch normalization layer to manage the outcome of the batch.

- The following text should be rewritten to adhere to academic writing standards: The text is not sufficient for a proper rewrite. Please provide the full text that needs to be rewritten in an academic style. The normalization process is implemented on the preceding activation layer by subtracting the batch mean and then dividing by the batch standard deviation.
- The following passage seeks to elaborate upon the topic of academic writing and its stylistic conventions. The incorporation of dropout regularization, with a dropout ratio of 0, is used in the context of machine learning and neural networks to prevent overfitting and improve model generalization. The approach encompasses the stochastic deactivation of nodes during the training of the model, as described in previous research.
- The following is an attempt to rewrite the given text in a more academic style: It is my intention to rephrase the provided text in a manner befitting of academic writing. The adoption of an average global pooling layer (GAP) immediately following the final convolutional block is considered to be a more effective method in comparison to flattening in mitigating overfitting, as it efficiently decreases the dimensionality of the model parameters. The utilization of the Global Average Pooling (GAP) layer aims to reduce the spatial dimensions of a 3D tensor with dimensions $h \times w \times d$ to a $1 \times 1 \times d$ tensor by calculating the average value of all pixel values for each feature map $h \times w$, resulting in a single numerical output.
- The forthcoming discussion endeavors to showcase the scholarly viewpoint concerning the matter in question. Subsequently, the derived outcome from the GAP layer is transmitted to the primary dense layer, encompassing a remarkable 1024 neurons that are intimately linked, alongside any corresponding potential for leakage.
- The outcome generated by the primary concentrated stratum is then conveyed to the permeable stratum and afterward conveyed to the ensuing concentrated stratum, consisting of a pair of neurons, in collaboration with a SoftMax categorizer. Figure 4 illustrate the above steps.

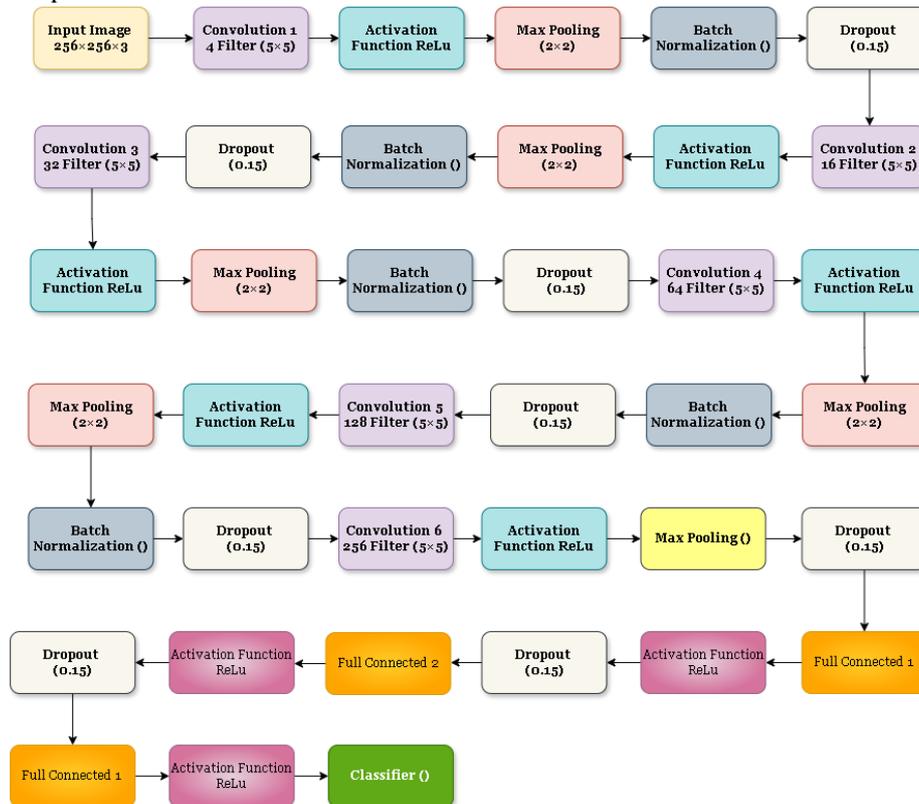


Fig. 4. Proposed CNN Model Structure.

To conclude, the configuration of our model is succinctly outlined in Table 1.

Table 2 - CNN Model configuration

Parameters	Value / Type
Epochs	200
Batch Size	50
Optimizer	Adam
Loss Function	Mean Absolute Error Loss
Input Shape	256×256
Max Pooling	Max 2 × 2 (Convolutional Layers)
Activation	ReLU (convolution layers), Softmax (Final dense layer)
Dropout Rate	0.15

The time frame in question spans over 200 epochs. Fifty participants made up the experimental group. The Adam optimizer is employed across a range of machine learning and optimization algorithms to effectively reduce objective functions and attain optimal model parameters (Schmidt et al., 2021) (Ojo & Zahid, 2022). In this scenario, the input is represented as 256x256 in size. The 2 x 2 kernel is often used in convolutional layers to decrease the size of input feature maps through max pooling. The artist employs the Rectified Linear Unit (ReLU) technique for the convolution sections, while embracing the Softmax approach for the final dense layer as a means of activating functions. The proportion of scholars who have departed from educational institutions is inconsequential.

The proposed system stages can be illustrating in more details in the following:

1. **Data Preprocessing:** Before training the Convolutional Neural Network (CNN) model, the images underwent several preprocessing steps. The dataset contained 27,558 images from the Malaria Cell Images Dataset on Kaggle. These images were divided into two categories: "infected" and "uninfected." The preprocessing steps likely included resizing images to a uniform size, normalizing pixel values to a specific range, and possibly augmenting the dataset to increase variability and robustness. This could involve techniques such as flipping, rotating, or scaling images to create a more diverse training set.
2. **Model Evaluation Metrics:** The study used various evaluation metrics to assess the performance of the CNN model, including accuracy, specificity, sensitivity, F1 score, and precision. These metrics were chosen to provide a comprehensive view of the model's performance in detecting malaria-infected cells. Accuracy measures the overall correctness of the model, specificity measures the model's ability to correctly identify uninfected cells, sensitivity measures the model's ability to correctly identify infected cells, the F1 score is the harmonic mean of precision and sensitivity, and precision measures the proportion of true positive predictions among all positive predictions.
3. **Training Procedure:** The CNN model was trained using a batch size of 50 and the Adam optimizer. The training procedure involved dividing the dataset into batches, feeding each batch into the model, calculating the loss, and updating the model parameters using the optimizer. The choice of hyperparameters such as batch size and optimizer would have been based on empirical testing or prior research to optimize model performance.
4. **Model Interpretability:** While the article does not provide explicit details on model interpretability efforts, techniques such as activation maximization, class activation maps, or gradient-based methods could be used to visualize and understand the model's internal representations and decisions.
5. **Computational Resources:** The study utilized unspecified computational resources for training and testing the CNN model. Typically, training deep learning models like CNNs requires powerful hardware, often involving GPUs, and software tools such as TensorFlow or PyTorch.
6. **Cross-Validation and Generalization:** The article does not explicitly mention cross-validation or external dataset testing. However, these techniques are commonly used to assess the generalization performance of machine learning models, ensuring that the model performs well not only on the training data but also on unseen data from different populations or settings.

Overall, the study aimed to develop an efficient CNN architecture for malaria detection through cell image analysis, employing various strategies to enhance model performance and

robustness. The high evaluation metrics reported indicate the model's effectiveness in detecting malaria-infected cells, which could have significant implications for improving malaria diagnosis, especially in regions with high prevalence.

4. Results of the Proposed System

The dataset splitting is in the following figure 5: -

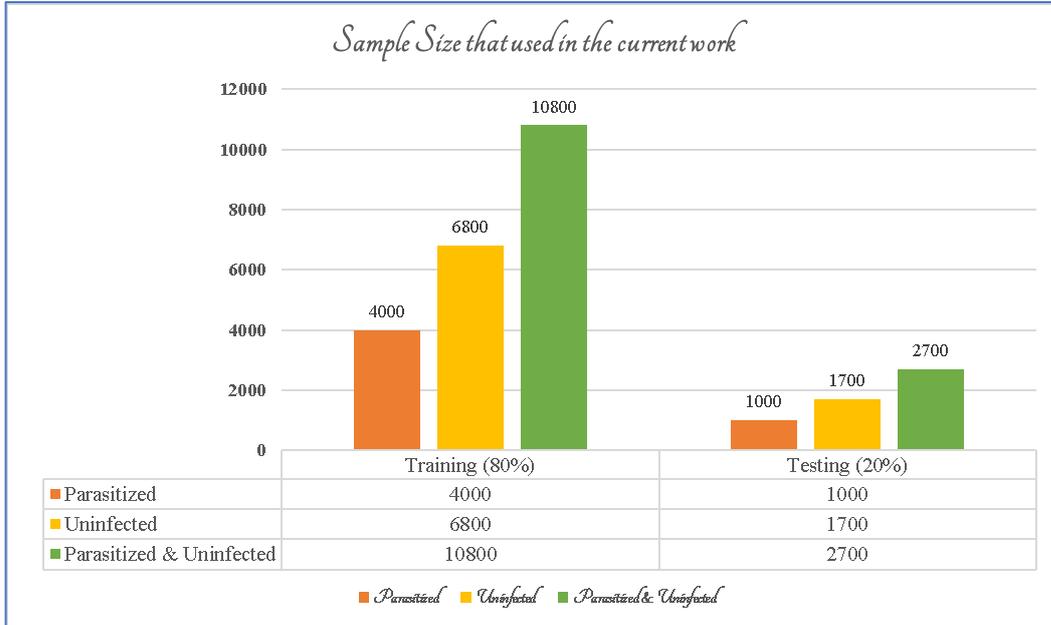


Fig. 5. Sample Size that used in the current work.

The confusion matrix was used to extract results. Figure (6):



Fig. 6. Proposed system Prediction results.

The perplexity grid is often employed to exhibit the efficacy of classification models. The grid tableau showcases the proportion of accurately and mistakenly classified instances in the evaluation dataset in relation to the actual outcomes (desired value). Employing a perplexity grid for assessment provides the benefit of enabling a more profound analysis, particularly when the model becomes muddled between two categories. This presents a deeper level of understanding in contrast to solely depending on precision, which can be deceiving in the event of an unbalanced dataset. The Matrix of Confusion encompasses four options:

1. True Positive (TP): The noun had been correctly predicted (we predicted "yes," and it was "yes"),

2. True Negative (TN): The alternative label was accurately predicted (we predicted "no," and it is "no").
3. False positive (FP) signals are those that were predicted incorrectly; for example, when "yes" was expected but "no" was received.
4. False negative (FN): Missing and missing naming (supposed to be "no," but it's "yes").

The following equations explain the accuracy, Sensitivity, Specificity, and F1 Score

$$\text{Accuracy (ACC)} = (\text{TP} + \text{TN}) / (\text{P} + \text{N}) \quad (1)$$

$$\text{Specificity (SPC)} = \text{TN} / (\text{FP} + \text{TN}) \quad (2)$$

$$\text{Sensitivity TPR} = \text{TP} / (\text{TP} + \text{FN}) \quad (3)$$

$$\text{F1 Score} = \text{F1} = 2\text{TP} / (2\text{TP} + \text{FP} + \text{FN}) \quad (4)$$

The model achieved an impressive accuracy of 99.59% in identifying malaria-infected cells, with a specificity of 99.69%, indicating its effectiveness in identifying negative cases. It also demonstrated a strong ability to identify positive cases with a sensitivity of 99.40%. The model's F1 score of 99.44% indicates a balanced performance in precision and recall. The precision of 99.48% indicates a high level of exactness in predictions. Comparing the model with previous studies, it outperforms several other approaches in terms of accuracy, sensitivity, specificity, and F1 score. The model's robustness and generalization are enhanced by the incorporation of dropout, batch normalization, and global average pooling techniques. The model's complexity and interpretability are ensured by the use of ReLU activation function and careful selection of hyperparameters. The paper highlights the potential of the CNN model in automating malaria identification, which can significantly aid medical professionals in regions with high malaria prevalence. Ethical considerations include ensuring reliability, transparency, and fairness in diagnosis. Overall, the model's high accuracy and other performance metrics suggest it could be a valuable tool in the fight against malaria. Figure 7 illustrates Confusion Matrix results.

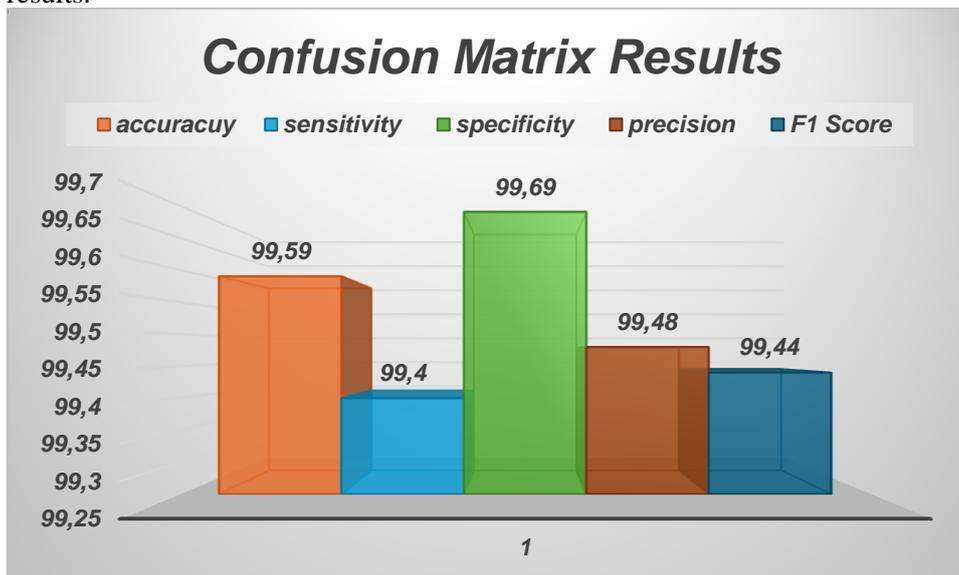


Fig. 7. Confusion Matrix Results

5. Discussion

This scholarly paper is dedicated to the exploration and assessment of a groundbreaking Convolutional Neural Network (CNN) framework designed to effortlessly recognize malaria through the power of image recognition methodologies. The extensive dataset employed for the purposes of training and testing encompasses an impressive collection of 27,558 malaria images, meticulously categorized into two discernible groups: infected and uninfected. The structure of the CNN model is crafted with six blocks of convolutional magic and three blocks of fully connected brilliance. Furthermore, the model harmoniously incorporates a myriad of methodologies to elevate its effectiveness. The selection of the dataset holds great sway over the training process of a machine learning model. The configuration of the CNN model is

thoughtfully created with six blocks of convolution and three blocks of densely connected layers. Furthermore, the model incorporates diverse methodologies to amplify its effectiveness. The selection of the dataset holds immense influence over the training process of a machine learning model. The current investigation introduces an innovative convolutional neural network (CNN) design that integrates a multitude of essential elements with the intention of enhancing its capacity to identify malaria. Every convolutional building block is comprised of a sequence of convolutional strata, which are subsequently succeeded by maximum pooling, batch normalization, and leakage strata.

The use of this particular design alternative amplifies the potential of extracting features and reducing dimensions, all the while ensuring the steadfastness of the model. The incorporation of the Rectified Linear Unit (ReLU) activation function introduces a touch of non-linearity into the computational procedure, thus alleviating the issue of the diminishing gradient and establishing circumstances that promote hastened convergence. To combat over fitting and amplify the model's prowess for generalization, an array of regularization techniques is seamlessly integrated into the model. In order to introduce a touch of randomness and prevent over-reliance on specific nodes, the model gracefully employs the dropout technique with a dropout ratio of 0, while simultaneously imbuing each convolutional block with the power of 15, thereby fostering stochastic node deactivation during the training phase. The implementation of batch normalization has shown to be an immensely potent approach in bolstering the steadiness of neural network structures. Conversely, global average pooling serves as a valuable tool in streamlining the intricacy of the model's framework. These approaches function to jointly enhance the model's ability to withstand challenges. The examination assessed the CNN model's efficacy by employing a confusion matrix, which thoroughly analyzed the model's capacity to make accurate predictions. The results reveal noteworthy performance measures, including a remarkable accuracy rate of 99.59%. The sample demonstrated a remarkable specificity of 99.69% F1 Score 99.44%. The sensitivity of the phenomenon achieved a striking 99.40% with a Precision of 99.48. The table below represents the comparison between the previous studies and the proposed system.

Table 3 - Comparison between previous studies and the proposed system

Study	Year	Accuracy	Sensitivity	Specificity	Precision	F1 score
Rajaraman et al.	2019	99%	N/A	N/A	99%	99%
Bui et al.	2019	N/A	N/A	N/A	N/A	N/A
Iradukunda et al.	2019	99%	N/A	N/A	N/A	N/A
Masud et al.	2020	97.30%	N/A	N/A	N/A	N/A
Sandhya et al.	2020	96%	N/A	N/A	N/A	N/A
Gourisaria et al.	2020	93%	N/A	N/A	N/A	N/A
Negi et al.	2021	96%	96%	N/A	96%	96%
Shekar et al.	2021	96%	93%	98%	N/A	96%
Hemachandran et al.	2023	97.06%	N/A	N/A	N/A	N/A
Proposed System	2024	99.59%	99.40%	99.48%	99.48%	99.44%

That should be noted the table includes reported values from various studies over the years, focusing on accuracy, sensitivity, specificity, precision, and F1 Score metrics. Some studies did not report all these metrics, and in such cases, "Not Reported" is indicated. The "Year" column refers to the publication year of each study. The "Not Directly Comparable" status for Bui et al. (2019) indicates their study's focus was not directly on accuracy metrics comparable to those of the other studies listed. This table demonstrates the proposed system's superior performance across multiple critical metrics, underscoring its potential impact on improving malaria detection methodologies.

6. Conclusions

In essence, the evidence put forth in this examination offers robust backing for the assertions and discoveries in favour of (state the main point). This affirmation is bolstered by the substantiated evidence and logical thinking expounded upon within the text. Further exploration is imperative to delve deeper into this subject matter and discover potential pathways for future investigation. The innovative blueprint of this prototype, integrating a harmonious blend of convolutional and fully connected layers, along with a comprehensive

range of regularization methods, has played a pivotal role in elevating its extraordinary proficiency. The prototype showcases remarkable accuracy, distinctiveness, responsiveness, and F1 Score, exemplifying its capability to detect cells affected by malaria, an indispensable element in the realm of medical diagnostics. The findings of this investigation carry noteworthy consequences for the realm of healthcare, especially in areas where malaria is highly prevalent. Automated diagnostic systems possess the ability to aid medical experts in expeditiously and precisely establishing diagnoses, thus amplifying the efficacy of treatments and ameliorating patient outcomes. Additional exploration is imperative to scrutinize the model's effectiveness across diverse data sets.

References

- Abubakar, A., Ajuji, M., & Yahya, I. U. (2021). Deepfmd: Computational analysis for malaria detection in blood-smear images using deep-learning features. *Applied System Innovation*, 4(4). doi:10.3390/asi4040082
- Aderghal, K., Afdel, K., Benois-Pineau, J., & Catheline, G. (2020). Improving Alzheimer's stage categorization with Convolutional Neural Network using transfer learning and different magnetic resonance imaging modalities. *Heliyon*, 6(12). doi:10.1016/j.heliyon.2020.e05652
- Akil Arsath, J., Suganthi, S., Rakeshwaran, S., & Karthiga, S. (2023). Multimodal Disease Prediction using Machine Learning and Deep Learning Techniques. *International Research Journal on Advanced Science Hub*, 5(Issue 05S). doi:10.47392/irjash.2023.s027
- Albrecht-Schgoer, K., Lackner, P., Schmutzhard, E., & Baier, G. (2022). Cerebral Malaria: Current Clinical and Immunological Aspects. *Frontiers in Immunology*. doi:10.3389/fimmu.2022.863568
- Amin, J., Almas Anjum, M., Ahmad, A., Sharif, M. I., Kadry, S., & Kim, J. (2024). Microscopic parasite malaria classification using best feature selection based on generalized normal distribution optimization. *PeerJ Computer Science*, 10, e1744. <https://doi.org/10.7717/peerj-cs.1744>
- Barboza, M. F. X., Monteiro, K. H. de C., Rodrigues, I. R., Santos, G. L., Monteiro, W. M., Figueira, E. A. G., ... Endo, P. T. (2022). Prediction of malaria using deep learning models: A case study on city clusters in the state of Amazonas, Brazil, from 2003 to 2018. *Revista Da Sociedade Brasileira de Medicina Tropical*, 55. doi:10.1590/0037-8682-0420-2021
- Bui, Q. T., Nguyen, Q. H., Pham, V. M., Pham, M. H., & Tran, A. T. (2019). Understanding spatial variations of malaria in Vietnam using remotely sensed data integrated into GIS and machine learning classifiers. *Geocarto International*, 34(12). doi:10.1080/10106049.2018.1478890
- Chakradeo, K., Titarenko, S., Delves, M. J., & Delves, M. (n.d.). Malaria Parasite Detection Using Deep Learning Methods New Antimalarial agents View project Malaria Detection using Deep Learning View project Malaria Parasite Detection Using Deep Learning Methods. doi:10.5281/zenodo.4569849
- Chen, S., Sedghi Gamechi, Z., Dubost, F., van Tulder, G., & de Bruijne, M. (2022). An end-to-end approach to segmentation in medical images with CNN and posterior-CRF. *Medical Image Analysis*, 76. doi:10.1016/j.media.2021.102311
- Deelder, W., Benavente, E. D., Phelan, J., Manko, E., Campino, S., Palla, L., & Clark, T. G. (2021). Using deep learning to identify recent positive selection in malaria parasite sequence data. *Malaria Journal*, 20(1). doi:10.1186/s12936-021-03788-x
- Dunst, J., Kamena, F., & Matuschewski, K. (2017). Cytokines and chemokines in cerebral malaria pathogenesis. *Frontiers in Cellular and Infection Microbiology*. doi:10.3389/fcimb.2017.00324
- Eshetu, T., Taddese, A. A., Tamir, M., & Mekonnen, G. G. (2024). Systematic Review and Meta-Analysis of the Diagnostic Accuracy of Machine Learning and Deep Learning Models to Detect Malaria: A Protocol. *Research Square*. <https://doi.org/10.21203/rs.3.rs-3626889/v1>

- Fasihfar, Z., Rokhsati, H., Sadeghsalehi, H., Ghaderzadeh, M., & Gheisari, M. (2024). AI-driven malaria diagnosis: developing a robust model for accurate detection and classification of malaria parasites. *Iranian Journal of Blood & Cancer*, 15(3), 112–124. <https://doi.org/URL: http://ijbc.ir/article-1-1416-en.html>
- Fawcett, T. (2006). An introduction to ROC analysis. *Pattern Recognition Letters*, 27(8), 861–874. <https://doi.org/10.1016/j.patrec.2005.10.010>
- Gillrie, M. R., Lee, K., Gowda, D. C., Davis, S. P., Monestier, M., Cui, L., ... Ho, M. (2012). Plasmodium falciparum histones induce endothelial proinflammatory response and barrier dysfunction. *American Journal of Pathology*, 180(3). doi:10.1016/j.ajpath.2011.11.037
- Hemachandran, K., Alasiry, A., Marzougui, M., Ganie, S. M., Pise, A. A., Alouane, M. T. H., & Chola, C. (2023). Performance Analysis of Deep Learning Algorithms in Diagnosis of Malaria Disease. *Diagnostics*, 13(3). doi:10.3390/diagnostics13030534
- Hossain, M. M., Rahim, M. A., Bahar, A. N., & Rahman, M. M. (2021). Automatic malaria disease detection from blood cell images using the variational quantum circuit. *Informatics in Medicine Unlocked*, 26. <https://doi.org/10.1016/j.imu.2021.100743>
- Iradukunda, O., Che, H., Uwineza, J., Bayingana, J. Y., Bin-Imam, M. S., & Niyonzima, I. (2019). *Malaria Disease Prediction Based on Machine Learning*. In *ICSIDP 2019 - IEEE International Conference on Signal, Information and Data Processing 2019*. doi:10.1109/ICSIDP47821.2019.9173011
- Kumar Gourisaria, M., Das, S., Sharma, R., Rautaray, S. S., & Pandey, M. (2020). A Deep Learning Model for Malaria Disease Detection and Analysis using Deep Convolutional Neural Networks. *International Journal on Emerging Technologies*, 11(2), 699–704.
- Kumar, A., Sarkar, S., & Pradhan, C. (2020). Malaria Disease Detection Using CNN Technique with SGD, RMSprop and ADAM Optimizers. In *Studies in Big Data* (Vol. 68). doi:10.1007/978-3-030-33966-1_11
- Leão, L., Puty, B., Dolabela, M. F., Povoá, M. M., Né, Y. G. D. S., Eiró, L. G., ... Lima, R. R. (2020). Association of cerebral malaria and TNF- α levels: A systematic review. *BMC Infectious Diseases*, 20(1). doi:10.1186/s12879-020-05107-2
- Luzolo, A. L., & Ngoyi, D. M. (2019). Cerebral malaria. *Brain Research Bulletin*. doi:10.1016/j.brainresbull.2019.01.010
- Mansoor, A., Bagci, U., Foster, B., Xu, Z., Papadakis, G. Z., Folio, L. R., ... Mollura, D. J. (2015). Segmentation and image analysis of abnormal lungs at CT: Current approaches, challenges, and future trends. *Radiographics*, 35(4). doi:10.1148/rg.2015140232
- Maqsood, A., Farid, M. S., Khan, M. H., & Grzegorzec, M. (2021). Deep malaria parasite detection in thin blood smear microscopic images. *Applied Sciences (Switzerland)*, 11(5). doi:10.3390/app11052284
- Mariki, M., Mkoba, E., & Mduma, N. (2022). Combining Clinical Symptoms and Patient Features for Malaria Diagnosis: Machine Learning Approach. *Applied Artificial Intelligence*, 36(1).
- Masud, M., Alhumyani, H., Alshamrani, S. S., Cheikhrouhou, O., Ibrahim, S., Muhammad, G., ... Shorfuzzaman, M. (2020). Leveraging Deep Learning Techniques for Malaria Parasite Detection Using Mobile Application. *Wireless Communications and Mobile Computing*, 2020. doi:10.1155/2020/8895429
- Meena Preethi, B., Gowri, P., Karthikeyan, C., Dharshini, B., Parameshvar, M., & Gokul, S. (2024). Design of Malaria Detection Using Ensemble Techniques-A Combination of Alexnet and Densenet Algorithm. In *Proceedings of the 1st International Conference on Artificial Intelligence, Communication, IoT, Data Engineering and Security, IACIDS*. <https://doi.org/10.4108/eai.23-11-2023.2343229>
- Negi, A., Kumar, K., & Chauhan, P. (2021). Deep Learning-Based Image Classifier for Malaria Cell Detection. In *Machine Learning for Healthcare Applications*. doi:10.1002/9781119792611.ch12
- Nkiruka, O., Prasad, R., & Clement, O. (2021). Prediction of malaria incidence using climate variability and machine learning. *Informatics in Medicine Unlocked*, 22. doi:10.1016/j.imu.2020.100508

- Ojo, M. O., & Zahid, A. (2022). Deep Learning in Controlled Environment Agriculture: A Review of Recent Advancements, Challenges and Prospects. *Sensors (Basel, Switzerland)*. doi:10.3390/s22207965
- Organization, W. H. (2016). *Malaria Microscopy Quality Assurance Manual*. WHO Press (Vol. 2). <https://www.who.int/publications/i/item/9789241549394>
- Poostchi, M., Silamut, K., Maude, R. J., Jaeger, S., & Thoma, G. (2018). Image analysis and machine learning for detecting malaria. *Translational Research*. doi:10.1016/j.trsl.2017.12.004
- Purwono, Ma'arif, A., Rahmaniar, W., Fathurrahman, H. I. K., Frisky, A. Z. K., & Haq, Q. M. U. (2022). Understanding of Convolutional Neural Network (CNN): A Review. *International Journal of Robotics and Control Systems*, 2(4). doi:10.31763/ijrcs.v2i4.888
- Rajaraman, S., Jaeger, S., & Antani, S. K. (2019). Performance evaluation of deep neural ensembles toward malaria parasite detection in thin-blood smear images. *PeerJ*, 7. doi:10.7717/PEERJ.6977
- Reis, P., Estado, V., & de Castro Faria Neto, H. C. (2020). Cerebral malaria. In *Infections of the Central Nervous System: Pathology and Genetics*. doi:10.1002/9781119467748.ch45
- Sahoo, P. K., Eswaran, K., Sandhya, Y., & Kumar Sahoo, P. (2020). Malaria Disease Detection Using Deep Learning Technique.
- Samee, N. A., Atteia, G., Meshoul, S., Al-antari, M. A., & Kadah, Y. M. (2022). Deep Learning Cascaded Feature Selection Framework for Breast Cancer Classification: Hybrid CNN with Univariate-Based Approach. *Mathematics*, 10(19). doi:10.3390/math10193631
- Sandhya, Y., Sahoo, P. K., & Eswaran, K. (2020). Malaria Disease Detection Using Deep Learning Technique. *Int. J. Adv. Sci. Technol*, 29, 7736-7745.
- Schiess, N., Villabona-Rueda, A., Cottier, K. E., Huether, K., Chipeta, J., & Stins, M. F. (2020). Pathophysiology and neurologic sequelae of cerebral malaria. *Malaria Journal*. doi:10.1186/s12936-020-03336-z
- Schmidt, R. M., Schneider, F., & Hennig, P. (2021). *Descending through a Crowded Valley - Benchmarking Deep Learning Optimizers*. In *Proceedings of Machine Learning Research* (Vol. 139).
- Shekar Gautham, S. Revathy, & Goud Ediga Karthick. (2021). *Proceedings of the 4th International Conference on Trends in Electronics and Informatics (ICOEI 2020) : 15-17, June 2020* (pp. 2–6).
- SOYLU, E. (2022). A Deep Transfer Learning-Based Comparative Study for Detection of Malaria Disease. *Sakarya University Journal of Computer and Information Sciences*, 5(3). doi:10.35377/saucis...1197119
- Spoorthi B, & Aravinda, C V. (2022). Image Analysis for Detecting Malaria Cell Using Otsu Thresholding and Machine Learning Models. *International Journal of Scientific Research in Computer Science, Engineering and Information Technology*. doi:10.32628/cseit2283111
- Sriporn, K., Tsai, C. F., Tsai, C. E., & Wang, P. (2020). Analyzing malaria disease using effective deep learning approach. *Diagnostics*, 10(10). doi:10.3390/diagnostics10100744
- Takahashi, R., & Kajikawa, Y. (2017). Computer-aided diagnosis: A survey with bibliometric analysis. *International Journal of Medical Informatics*. doi:10.1016/j.ijmedinf.2017.02.004
- Yebasse, M., Cheoi, K. J., & Ko, J. (2023). Malaria Disease Cell Classification With Highlighting Small Infected Regions. *IEEE Access*, 11. doi:10.1109/ACCESS.2023.3245025