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PAPER

A Deep Learning Approach for Malnutrition Detection

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ABSTRACT

The timely detection of malnutrition in children is of paramount importance, as it allows for early intervention and treatment. This proactive approach not only prevents further health deterioration but also fosters proper growth, minimizing the long-term consequences of malnutrition, such as stunted growth, impaired cognitive development, and increased vulnerability to diseases. Our work encompasses the creation of a new dataset comprising images of children in Healthy, Undernourished, Stunting, and Wasting categories. The core objective is to assess the deep learning model performance in classifying these children images. The experimentation is carried out by varying epochs, batch size, optimizers AdamW, Adamax, and RMSprop; and different values of the learning rate 0.1, 0.01, 0.001, and 0.0001 during model training. The model is trained on image dataset constructed by cleaning images generated by the stable diffusion model. The model is tested on randomly selected child images from websites. The model successfully classified two classes with 95% accuracy, 97.6% F1 score, precision 97.6%, and 97.6% recall with Adam optimizers, 0.0001 learning rate, and Batch size 4. Additionally, for the four-class categorization scenario, the study broadens the classification. The model achieved 88.87% accuracy, 90.3% recall, 90.2% precision, and an F1 score of 90% for four-class categorization with AdamW optimization, 0.0001 learning rate, and batch size 6. These results are satisfactory for prediction of malnutrition category in children.

KEYWORDS

ResNet18, malnutrition, deep learning, classification, optimization, good health and well-being

1 INTRODUCTION

Dietary deficiency is one of the major bottlenecks in improving economic and social growth. According to the World Health Organization (WHO), millions of children are suffering from stunting, wasting and overweight and the most prominent countries where highest degree of malnourished people were found are Asia and Africa (Central Sub-Saharan Africa) [1–2]. According to the Joint Child Malnutrition Estimates (JME) provided by the World Health Organization (WHO)

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in 2022 [3]: "Stunting has affected 22.3% of children under the age of 5 in the same year, severe wasting was observed in 13.7 million children under 5 years in 2022 and approximately 5.6% of children under 5 years were identified as overweight in 2022."

Nutrition plays a vital role in ensuring good health and promoting optimal human body development, particularly in children. Adequate calorie intake is essential to prevent malnutrition, which can have severe consequences on health, including an increased risk of heart disease, stroke, diabetes, and other health issues [4–5]. Achieving Good Health and Well-being is closely tied to proper nutrition. Key body parameters, assessed through Z-scores in anthropometric analysis, serve as crucial metrics for identifying and addressing malnutrition in children.

Height for Age (HAZ) is used to identify stunting, a condition where children fall significantly below the expected height for their age. Addressing stunting is essential for promoting Good Health and Well-being in children.

Weight for Height (WHZ) is utilized to identify wasting, which indicates that a child is substantially underweight for their age.

Weight for Age (WAZ) is a metric used to define underweight, signifying that a child weight is considerably lower than the expected weight for their age. Addressing underweight is essential to promote the good health and overall well-being of children.

By monitoring and addressing these anthropometric parameters, there is a opportunity to take significant steps toward achieving the Sustainable Development Goal of Good Health and Well-being for all children as established by the United Nations. Proper nutrition and the prevention of malnutrition are fundamental components of this goal. It is observed that, in most children, low to moderate malnutrition affects their growth and development at early ages. Diagnosing malnutrition at an early age reduces healthcare expenses and helps in maintaining good health [6]. In literature, several works have attempted to classify children in the categories ranging from malnourished to nourished based on machine learning (ML) algorithms. The challenges faced by ML algorithms are data collection and annotation. In computer vision, image classification is the most important task for any inference and convolutional neural networks (CNN) are the state-of-the- art techniques for image classification. CNNs eliminate the bottleneck in accuracy of classification by automating image feature extraction process and eliminating the need for handcrafted features extraction [7].

Children's images are classified as nourished or malnourished using AlexNet by fine-tuning the model through transfer learning technique. This model classifies child images as nourished or malnourished child image [8]. The utilization of web and mobile applications designed for child growth measurement and monitoring provides valuable guidance for parents and caregivers [9]. These tools offer insights into maintaining optimal child health, allowing for targeted nutritional interventions and support. This, in turn, enhances the prospects for a child with complete recovery and overall well-being. In rural areas, challenges arise when detecting child malnutrition due to limited access to healthcare facilities and resources, which are coupled with a lack of community awareness and education regarding malnutrition signs and consequences. The scarcity of specialized training, resources, and diagnostic tools hampers healthcare workers in rural regions from effectively addressing the malnutrition issue. Consequently, there is a pressing need for an automated tool to detect child malnutrition, enabling early intervention and improved healthcare outcomes.

In this study, a CNN model is employed to classify children's images into healthy and unhealthy categories based on visual appearance of images.

Following are the contributions of this research.

- This work provides a comprehensive review of the current state-of-the-art techniques for identifying malnutrition. It reveals that a majority of successful models rely on ML algorithms, often using demographic public survey data as their basis.
- Synthetic Children Dataset: In this study, a novel children dataset is constructed by synthetically generating child images. The Stable Diffusion text-to-image synthesis technique is utilized for this purpose.
- Web Scraping Tool: The paper introduces a custom web scraping script to collect real-world children's images from specific websites, enhancing the dataset with authentic data.
- This paper focuses on classification of child images as nutrition and malnutrition based on children image without depending upon other pathological records. Malnutrition category is further classified into stunting, wasting and overweight. This study demonstrates the effectiveness of ResNet18 for classifying child images, showcasing its performance through the application of transfer learning techniques. The performance of ResNet-18 is enhanced by fine-tuning the hyperparameters, namely, epochs, batch size, optimizers and learning rate.

The rest of the paper is organized as follows:

Section 2 gives a survey of state-of-the-art techniques for malnutrition identification in children; section 3 elaborates on the methodology of this work and gives a description of dataset and model with training details; section 4 presents experimental results and discussion; and section 5 provides conclusion and future scope.

2 LITERATURE SURVEY

In this section, a state-of-the-art technique survey summary is presented. The survey represents active research in continuous thrust, which aims at developing artificial intelligence model for identification of malnutrition in children. Child malnutrition was addressed using an ML approach in several papers that need child medical records. The malnutrition in the form of stunting and wasting was analyzed using conventional ML algorithms. It was found that tabular deep learning models of ML work well with satisfactory performance with Accuracy of 96.46% and AUC-ROC scores of 99.95% [1]. The J48, random forest (RF) and Naïve Baye algorithm were used for the detection of edematous malnutrition for the Afghanistan region children. Among these algorithms, RF gave the best accuracy of 97.14% and J48 gave considerably good results with an accuracy of 94.51%. These models were developed for malnutrition detection in children, which aids in health policy making by the government [4]. Artificial neural networks (ANN) were used to identify malnutrition in children between ages 0 and 59 months for Bangladeshi children's data. The results strongly recommended using ANN techniques for categorizing the children's condition into wasting, stunting and overweight. They recommended a model to be used by policy makers [5].

Insufficient muscle mass and low-fat levels in a newborn baby are indications of malnutrition. ML models are employed to predict malnutrition in newborns. In this study, UNICEF data was utilized for model training, and performance evaluation was conducted using z-scores as metrics. Among various ML models including KNN, SVM, Naïve Bayes, and logistic regression, logistic regression exhibited the highest model accuracy [10]. Malnutrition in women can lead to stunting and diabetes, which can affect children's health, resulting in low birth weight and compromised immunity. ML algorithms, including RF, Naïve Bayes, SVM, ANN, and decision trees, were explored. The results indicated that multinomial logistic regression (MLP) achieved the best results in terms of accuracy and area under the curve (AUC) [11]. Research has been conducted to study malnutrition in children under five years of age. The data was collected by conducting the survey in Ethiopia. Malnutrition in children is predicted by utilizing Logistic Regression (LR), NN, RF and elastic net ML algorithm. Among these algorithms, the RF algorithm performance is satisfactory in predicting malnutrition [12]. Similar work has been done by other researchers where the model was developed using ML techniques to forecast malnutrition in children under five. Several methods, including LR, RF, k-nearest neighbors (k-NN), support vector machine (SVM), logistic discriminant analysis (LDA), and logistic regression were used to predict the nutritional status of children based on data from the Bangladesh Demographic and Health Survey (BDHS).

The performance of the models was evaluated using metrics, sensitivity, accuracy, Cohen's kappa statistic, and specificity. With a sensitivity of 94.66%, specificity of 69.76%, accuracy of 68.51%, and Cohen's kappa of 0.2434, the RF algorithm outperformed the other models [13].

The k-NN model was developed especially to identify stunting in children. The primary aim of this model was to consistently observe the growth and development through the examination of various body index components [14]. To assess stunting in children under the age of five, machine learning (ML) techniques were utilized on the Zambia Demographic Health Survey (ZDHS) dataset. In this study, the algorithms XG Boost (XgB), Naïve Bayes (NB), RF, and Logistic Regression (LR) were employed.

To enhance the performance of the model, classifications and the expected probabilities were calibrated for a RF based model. The results revealed that the RF algorithm consistently outperformed other models in terms of classification accuracy, with the Naïve Bayesian model exhibiting the lowest accuracy [15].

KNN ML models were used to identify childhood malnutrition early on. The Euclidean distance was used to evaluate the performance of the KNN model. The KNN algorithm's simplicity and convenience of implementation were utilized in the work. The Puskesmas Ubung dataset was used to test the model [16]. A decision tree that made use of the Gini index metric was created in order to address problems associated with Protein-Energy Malnutrition (PEM), which results in stunting, wasting, and underweight in babies [6].

Body Mass Index (BMI) serves as a widely adopted tool for assessing whether an individual's weight aligns with the appropriate range for their height. In cases of malnutrition, BMI is frequently employed to detect undernutrition or inadequate calorie consumption, leading to the manifestation of a lower BMI. The researchers of [17], proposed a method that investigates the potential of facial images for malnutrition and obesity identification through the analysis of BMI and body weight. It employs a regression method based on a 50-layer residual network and utilizes Multi-task Cascaded CNN for face detection. The study focuses on evaluating BMI, age, and gender from real-time facial images, which are traditional indicators of malnutrition and obesity. While prior studies have predominantly concentrated on full-body images, this work emphasizes the underexplored significance of facial images in estimating height, weight, and BMI. The dataset is meticulously curated, incorporating metadata containing height, weight, age, and gender information.

Nutritional disorders can be monitored by using measurements such as weight and height. One such work is proposed by the researchers of [18], where their research delves into the utilization of learning models, specifically support vector regression (SVR), Gaussian process, and ANN, to estimate height and weight based on anthropometric measurements. These models display superior predictive accuracy compared to conventional linear regression methods. Notably, the predictions remain consistent across diverse ethnicities and genders when multiple anthropometric parameters are considered.

Maintaining proper nutrient balance is critical, particularly in infants, to prevent long-term health issues. An IoT-based system called 'Smart-Log' is introduced by researchers of [19] for automated nutritional monitoring in both home and daycare settings. Smart-Log employs advanced neural networks and Bayesian algorithms to predict meal content, achieving an impressive accuracy of 98.6% in experimental assessments. This innovation holds promise for promoting healthy infant development. The hue of human nails can serve as a diagnostic indicator for various medical conditions within the healthcare field. Researchers of [20–21] proposed the method to detect malnourishment by taking the nail images as input, which is accomplished using CNN.

Stunting, a severe consequence of early childhood malnutrition, leads to lasting physical and cognitive damage. Early identification is vital for public health. In work [22], researchers analyzed Ethiopian Demographic Health Survey (EDHS) data using a generalized linear mixed model to explore determinants of child stunting and interconnections among risk factors. The results indicate a positive association between a child's age and stunting, with children aged 24 to 59 months and 12 to 23 months facing a higher risk compared to those aged 0 to 11 months. These findings underscore the importance of timely interventions to address stunting and promote child health. A Decision Support System has been developed by the researchers of [23] for the early identification of malnutrition risk, utilizing data gathered through a mobile health (m-health) application designed for monitoring nutritional status and body composition. Multiple ML models were utilized, using the Mini Nutritional Assessment rating scale as the ground truth. Techniques like Synthetic Minority Oversampling Technique (SMOTE) and cost-sensitive learning were applied to handle dataset imbalances. The results demonstrated that the most effective ML models achieved a median accuracy of 94% and recall of 92% for predicting malnutrition risk.

Researchers of [8] employed deep learning technique AlexNet for classification of child images based on the nutrition criteria. Deep learning CNN architectures are powerful techniques for classification of images, a few of such works are: deep fake image detection [24], medical image classification and segmentation [25–26], classification of food images and nutrition analysis [27] and brain stroke prediction [28]. Table 1 summarizes the literature survey of malnutrition identification briefly.

Table 1. A brief summary of the state-of-art work done in malnutrition identification

Reference	Objective of Work	Dataset	Models Used	Results
[1]	Predicting the key determinants of malnutrition	Survey data Indian Demographic and Health Survey (IDHS) datasets	Automated ML algorithms	96.46%
[4]	Predicting the extent of edematous malnutrition's seriousness	Children data "Entry Date, Age, MUAC, Weightz, Height, WHZ, Cured, Death, Refer_date, Stay_length, Weight_gain, Avg_weight_gain"	RF, J48	RF – 97.41% J48 – 94.51%
[5]	Malnutrition in children aged between 0–59 months	The BDHS dataset encompasses birth records and household information records spanning all seven divisions within Bangladesh	ANN, SVM	ANN For class Stunting – 86% Underweight – 70% Wasting – 67.3% SVM For class Stunting – 84.93% Underweight – 67.75% Wasting – 63.34%
[8]	Malnutrition Detection	Children image dataset	AlexNet	96%
[10]	Malnutrition in newborn Infants	UNICEF numerical dataset	Logistic Regression SVM KNN	Logistic Regression – 95.9% SVM – 97.4% KNN – 95.9%
[11]	Predicting malnourished women	BDHS	RF	RF – 81.4%
[12]	Investigate and analyze the determinants of undernutrition among children under five in Ethiopian administrative regions	EDHS	GLM, Ridge, Lasso, Elastic-net	Accuracy (95% CI) GLM – 0.356 (0.344, 0.369) Ridge – 0.649 (0.636, 0.661) Lasso – 0.683 (0.671, 0.695 Elastic-Net – 0.682 (0.670, 0.694) NN – 0.656 (0.644, 0.668) RF – 0.688 (0.676, 0.700)
[13]	Prediction of malnutrition among children under the age of five in Bangladesh	BDHS	KNN, LDA	KNN – 65.59% LDA – 68.57% SVM – 66.74% RF – 68.23% LR – 68.13%
[14]	Diagnosing malnutrition in children	Collected data through survey	KNN	–
[15]	Categorizing stunting in children under the age of five in Zambia	ZDHS	LR, RF, SVC, XgB, NB,	LR – 45.9% RF – 61% SVC – 55.8% XgB – 58.51%
[16]	Classification of Malnourished Toddlers	Puskesmas Ubung dataset	KNN	91%
[17]	Prediction of BMI from facial images	Face dataset	CNN	In terms of MAE for prediction of: BMI – 5.02 Age – 7.164

(Continued)

Table 1. A brief summary of the state-of-art work done in malnutrition identification *(Continued)*

Reference	Objective of Work	Dataset	Models Used	Results
[18]	Prediction of height and weight	NHANES III ANSUR	Linear Regression, Support Vector, Gaussian Process, NN	In terms of CI for prediction of: **i)** Waist circumference Linear Regression – 74% Support Vector: 79% Gaussian Process – 79% NN – 79% **ii)** Waist, Height, Buttock circumference Linear Regression – 92% Support Vector: 94% Gaussian Process – 94% NN – 94% **iii)** Waist, Height, Butt., Thigh, Arm Circumference Linear Regression – 96% Support Vector: 98% Gaussian Process – 98% NN – 98%
[19]	Identifying nutritional characteristics in food components and recommending potential future meals or recipes	Open Food dataset	Smart-Log using NN and Bayesian Network	98.6%
[20]	Detecting diseases within the human body through the analysis of nail images captured from human fingers and interpreting data derived from elementary aspects of nail color	Nail image dataset	CNN	Between 90% to 95%
[21]	Detection of malnutrition	Nail image dataset	CNN	–
[23]	Malnutrition Risk Assessment	m-Health	RUSBoost	RUSBoost – 93.1%

The investigation provides a glimpse into diverse machine learning models previously examined by researchers for malnutrition identification. Various matching learning algorithms, such as logistic regression, Random Forest, decision tree, XGboost, KNN, etc., were tested using demographic health survey data from countries like Bangladesh, Afghanistan, Africa, and Zambia. The extensive examination of malnutrition detection reveals that existing research primarily relies on survey data.

The literature survey indicates a noticeable gap in studies focusing on malnutrition detection through visual appearance. The proposed work aims to address this gap by concentrating on the classification of malnourished children using a convolutional neural network based on their visual characteristics.

3 PROPOSED METHOD

This research focuses on 2 class and multi-class classifications for malnutrition detection in pediatric populations based on the child image. Figure 1 depicts the flow of the proposed model.

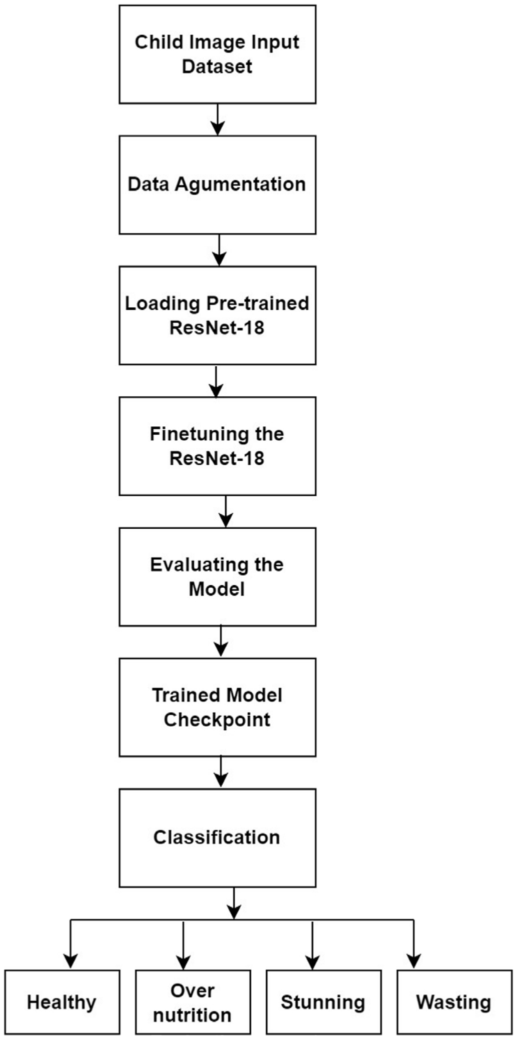

Fig. 1. Flow of proposed work

3.1 Dataset creation

In the context of malnutrition detection, dataset creation involves gathering a comprehensive collection of data samples representing various nutritional states. This can be achieved through a combination of synthetic data generation and web scraping. Synthetic data generation entails fabricating data instances that mimic real-world scenarios of malnutrition, encompassing parameters like age and health indicators. This synthesized data supplements the limited real-world data and ensures a more balanced dataset. Simultaneously, web scraping plays a pivotal role in acquiring authentic information from online sources such as medical journals, nutritional databases, and health organization reports. The accuracy of the model is increased by extracting data from these sources, which guarantees the dataset's timeliness and relevancy.

The dataset was created by combining web scraping with the use of a pre-trained model called Stable-Diffusion. The photographs of the youngsters are categorized as both nutritionally sound and malnourished. To synthesize images guided by specified content descriptions, Stable-Diffusion—a model pre-trained for producing images based on textual descriptions—is used [29]. Furthermore, this study uses the Stable-Diffusion pre-trained model to create a dataset of artificially malnourished children's photos.

Equation (1) is used to compute the loss for a standard diffusion model (DM).

$$L_{DM} = E_{x,t,\epsilon}[\| \epsilon - \epsilon_{\theta}(x_t, t) \|^2] \tag{1}$$

Equation (2) therefore gives the loss for a latent diffusion model (LDM) given an encoder E and a latent representation z.

$$L_{LDM} = E_{\epsilon(x),t,\epsilon}[\| \epsilon - \epsilon_{\theta}(z_t, t) \|^2] \tag{2}$$

Stable Diffusion is a transformer model that uses a diffusion process to produce high-quality images from textual descriptions. Utilizing a text encoder, it transforms a textual prompt into a latent text representation. This latent representation guides the diffusion process, ensuring that the resulting image aligns with the supplied text.

The malnutrition dataset comprises child images categorized into four groups: Healthy, Undernourished, Stunting, and Wasting, with each class containing 500 training images, resulting in a total of 2000 child images for the training dataset. Additionally, there are 150 validation images for each class, totaling 600 images for the validation dataset. These images were acquired through two distinct methods. Firstly, a stable diffusion model, a form of generalization model, was employed to iteratively refine original images by introducing noise, producing realistic composite images. Secondly, web scraping, utilizing the "Beautiful Soup" tool, was employed to gather additional images from the internet. Web scraping is a method for gathering pertinent photos from the internet by extracting data from it. The dataset is intended for use in the creation and evaluation of machine learning algorithms for the classification of nutritional states based on picture data. The validation of application of these images in exploring design of a deep learning model is approved by the medical practitioner.

3.2 Classification using ResNet-18

The amount of the dataset used in the proposed work is constrained. Small datasets present difficulties for deep neural network training, necessitating careful thought when choosing the right architecture. This exploration serves as proof-of-concept evaluation and gives insight future directions.

Many important considerations influenced the selection of the ResNet-18 model. Notably, ResNet-18 balances computational efficiency with model complexity, which makes it a good choice in situations with sparse data. With skip connections and residual blocks, its architectural design tackles issues like vanishing gradients, which are especially important when working with smaller datasets [30–31].

ResNet-18's architecture has demonstrated efficacy in handling limited data scenarios. By leveraging skip connections, the model is better equipped to learn meaningful representations from a smaller number of examples, mitigating the risk of overfitting.

Within conventional feedforward neural networks, there is a sequential progression of data flow, wherein the output from one layer serves as the input for the subsequent layer. ResNet-18 employs residual blocks. A residual connection establishes an alternative pathway for data to traverse through subsequent segments of the neural network, circumventing specific intermediate layers. For a sequence of layers denoted as layer i to layer i + n, where F represents the function embodied by these layers, and let x be the input for layer i. In the conventional feedforward context, x would traverse through these layers sequentially, producing the outcome F(x) at layer i + n. A residual connection, which circumvents these layers, is shown in Figure 2.

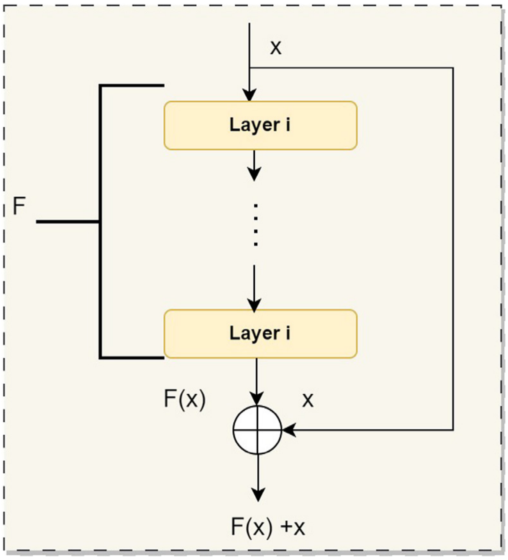

Fig. 2. Residual connection

This adaptability to limited data scenarios is crucial for the success of our research, where obtaining a large dataset is impractical or cost prohibitive. ResNet-18 offers substantial potential for transfer learning. We leveraged pre-trained weights on a larger dataset, allowing the model to capture generic features that can be fine-tuned for our specific task. This not only accelerates the training process but also enhances the model's ability to generalize patterns from the limited data set available for this research.

The incorporation of residual learning in deeper networks addresses the issue of accuracy degradation encountered in such networks. In conventional networks, numerous layers are sequentially arranged to directly acquire the intended mapping. However, in residual networks, these layers are organized to learn residual mapping. The mapping function, represented as $H(x)$, is approximated by a few stacked layers. The conceptual basis of residual learning posits that if a set of nonlinear layers can asymptotically approximate a complex mapping function, they can likewise asymptotically estimate the residual function denoted as $F(x)$ [32]. The fundamental mapping is expressed as shown in Equation 3.

$$H(x) = F(x) + x \tag{3}$$

The residual function is shown in Equation 4.

$$F(x) = H(x) - x \tag{4}$$

The layers arranged in a stacked manner explicitly focus on learning the residual function $F(x)$ rather than directly learning the original function $H(x)$.

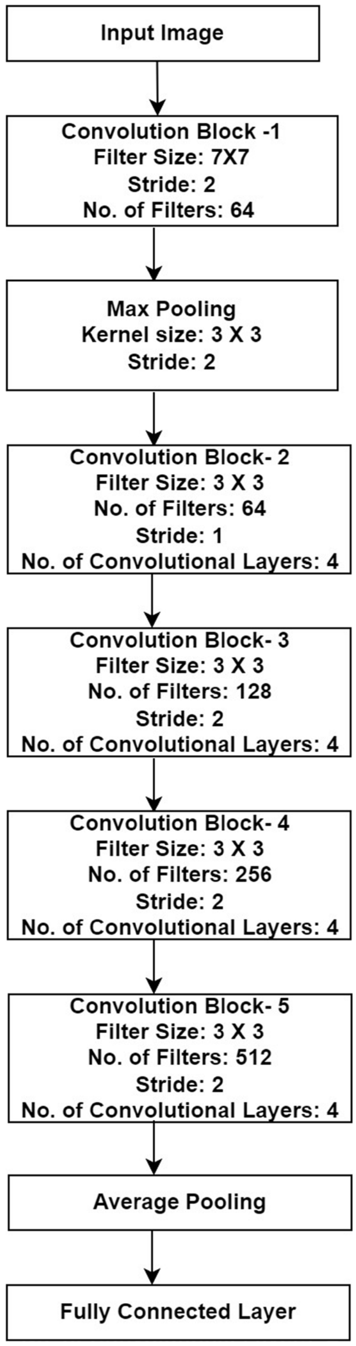

Fig. 3. Architecture of ResNet-18

ResNet incorporates a shortcut connection within its architecture, establishing a link from the input of the nth layer to the $(n + i)$th layer. The ResNet structure comprises multiple residual building blocks. Figure 3 represents the configuration of ResNet-18 used in this work. The ResNet-18 consists of 17 convolutional layers, a fully connected layer and SoftMax layer for classification. The convolutional layer plays a major role in feature extraction. The convolutional layers utilize 3×3 filters, and the network is structured to maintain consistency: if the output feature map size remains unchanged, the layers maintain the same number of filters. However, in instances where the output feature map is halved, the number of filters in the layers is doubled. If the input layer consists of X number of units and the size of the kernel is Y, then the convolutional layer consists of $X-Y+1$ units. The representation of the output of the lth convolutional layer is given in Equation 5.

$$C_i^{l,j} = \sigma\left(b_j^l + \sum_{y=1}^{Y} w_y^{l,j} d_{i+y-1}^{l-1,j}\right) \tag{5}$$

Where l is the index of the layer, σ is the activation function, b_j represents the bias term for the jth feature map, Y is the size of the kernel/filter and w_y^j represents the weight of the yth indexed kernel for the jth feature map.

The down-sampling is achieved through max pooling layer. An average pooling layer followed by a fully connected layer with softmax activation function. Equations 6, 7 and 8 depict max, pooling layer and softmax classification layer.

$$P_{i,max}^{l,j} = \underset{r \in Y}{max}\left(f_{(i-1)\times S+r}^{l-1,j}\right) \tag{6}$$

$$P_{i,avg}^{l,j} = \underset{r \in Y}{avg}\left(f_{(i-1)\times S+r}^{l-1,j}\right) \tag{7}$$

Y, S, and r represent the size, stride, and index, respectively.

$$(c|f) = \underset{c \in C}{\text{argmin}} \frac{exp(f^{M-1}w^M + b^M)}{\sum_{j=1}^{N_c} exp(f^{M-1}w_j)} \tag{8}$$

Where c represents the class label, M indicates the index of the last layer and FC represents the total number of classes, f represents the feature vector, and b represents the bias of the output layer. During forward propagation, the network predicts the probability of the input feature vector belonging to the class and computes the error value using the specific loss function L. During back propagation, weights (w) are updated using the gradient descent technique. This training process will be terminated when it exceeds the given number of epochs or reaches the minimum error value than the threshold error.

The ResNet-18 is employed to perform binary classification and multi-classification classes. In case of binary classification, the image will be classified into one of the nutrition or malnutrition classes. In case of multi-class classification, the input image will be classified into the one of the classes among healthy, over nutrition, stunting and wasting.

4 EXPERIMENTAL SETUP

The experiment is conducted using Jupiter notebook, PyTorch library for deep learning tasks on Windows 10 operating system.

4.1 Dataset

The provided dataset encompasses a comprehensive range of child images, divided into four distinct classes: "Healthy," "Over-nutrition," "Stunting," and "Wasting." Each class represents the specific nutritional state of a child. Within these classes, there is a consistent distribution of images to facilitate robust training and validation of machine learning models. For each of the four categories, the dataset comprises a total of 500 images designated for training purposes. The basis for machine learning models' learning and improvement in classifying and categorizing child photos based on their nutritional state is provided by these images. Furthermore, 150 separate photos are kept aside for confirmation. This validation set serves as an independent standard by which to evaluate the correctness and performance of the models on fresh, untested data. All told, there are 2,600 child photos in the dataset, which are divided into four different categories: "Healthy," "Overnutrition," "Stunting," and "Wasting." The foundation for developing and accessing machine learning algorithms intended to precisely identify and classify various nutritional statuses in children is laid by this well-organized and diversified dataset. These kinds of datasets are essential for creating efficient models that support early detection.

4.2 Classification using ResNet-18

With a ratio of 60% for training, 20% for testing, and 20% for validation, the image dataset has been divided into training, testing and validation sets. The ResNet-18 model is trained with the following parameters: Epoch 100, Batch Size 4 and Cross-entropy loss function. The model is finetuned by varying the optimizers and learning rate. Adam, AdamW, Adamax, RMSProp, and SGD optimizers are employed; and 0.1, 0.01, 0.001 and 0.001 learning rates are tested for classification. Table 2 depicts the hyperparameters used in this experiment.

Table 2. Hyperparameters used to train ResNet-18

Hyperparameters	Values
Epoch	50, 100, 150
Learning rate	0.1, 0.01, 0.001, 0.0001
Optimizers	AdamW, Adamax and RMSProp
Batch size	2, 4, 6, 8
Loss function	Categorical cross entropy
Classification	Softmax

The results are evaluated using precision, recall and F1-score. Table 3 depicts the performance analysis of ResNet-18 with Adam optimizer by varying the learning rate. The results show that the model performs good for learning rate 0.0001 with 82.99% and 95.53% of training and testing accuracy, respectively.

Table 3. Model evaluation metrics for 2-class classification

Training Parameters	Training Loss	Training Accuracy (%)	Validation Loss	Validation Accuracy (%)	Precision	Recall	F1-Score	Training Complete Time
Batch size = 4, Learning rate = 0.1, Optimizer = Adam	0.5659	72.32	0.5103	76.54	0.92	0.87	0.9	13m 59sec
Batch size = 4, Learning rate = 0.01, Optimizer = Adam	0.4974	79.59	0.22	88.89	0.93	0.91	0.95	14m 30sec
Batch size = 4, Learning rate = 0.001, Optimizer = Adam	0.325	82.99	0.149	95.53	0.975	0.9756	0.975	12m 34sec

Table 4 summarizes the outcomes of three distinct experiments conducted during the training of a ResNet-18 model for a 4-class child image Malnutrition classification task. Each row corresponds to a unique experiment, while it represents the performance metrics along with the training settings for each case with a Learning rate of 0.1 with a different optimizer. Similarly, Tables 5, 6 and 7 depict the evaluation for learning rate 0.01, 0.001 and 0.0001, respectively.

Table 4. Model evaluation metrics for 4-class classification with learning rate 0.1 and batch size 4

Optimizer	Training Loss	Training Accuracy (%)	Validation Loss	Validation Accuracy (%)	Precision	Recall	F1-Score	Training Complete Time
AdamW	1.2833	40.43	1.283	44.73	0.530	0.4624	0.411	66m 51sec
Adamax	1.1538	49.53	1.0745	55.08	0.5685	0.5632	0.5540	62m 43sec
RMSprop	1.2792	39.84	1.2287	42.58	0.4668	0.4513	0.4294	61m 32sec

Table 5. Model evaluation metrics for 4-class classification with learning rate 0.01 and batch size 4

Optimizer	Training Loss	Training Accuracy (%)	Validation Loss	Validation Accuracy (%)	Precision	Recall	F1-Score	Training Complete Time
AdamW	1.3834	27.73	1.384	24.41	0.063	0.25	0.101	61m 45sec
Adamax	1.1774	46.91	1.085	55.47	0.532	0.553	0.522	60m 49sec
RMSprop	1.1990	45.97	1.100	48.63	0.474	0.505	0.474	57m 57sec

Table 6. Model evaluation metrics for 4-class classification with learning rate 0.001 and batch size 4

Optimizer	Training Loss	Training Accuracy (%)	Validation Loss	Validation Accuracy (%)	Precision	Recall	F1-Score	Training Complete Time
AdamW	1.093	53.31	0.9329	60.74	0.6498	0.6517	0.6433	61m 4sec
Adamax	0.462	82.55	0.3554	86.33	0.8756	0.8726	0.8713	62m 4sec
RMSprop	1.179	46.27	1.064	49.22	0.4896	0.5161	0.4891	58m 40sec

Table 7. Model evaluation metrics for 4-class classification with learning rate 0.0001 with batch size 4

Optimizer	Training Loss	Training Accuracy (%)	Validation Loss	Validation Accuracy (%)	Precision	Recall	F1-Score	Training Complete Time
AdamW	0.4214	85.1	0.28	88.87	0.903	0.902	0.902	61m 6sec
Adamax	0.5259	80.08	0.3476	87.30	0.885	0.879	0.880	62m 18sec
RMSprop	0.4378	83.89	0.3509	86.52	0.8919	0.888	0.889	58m 6sec

The careful observation of Tables 4, 5, 6, and 7 demonstrates that the model performs well with a learning rate of 0.0001, thanks to its small step size and the use of the AdamW optimizer. AdamW handles weight decay more effectively than Adam and RMSProp. Figures 4, 6 and 8 depict the training and validation loss of ResNet-18 by varying learning rates with Adamax, AdamW and RMSProp optimizers. For all optimizers, training and validation loss converged faster when the learning rate is 0.0001.

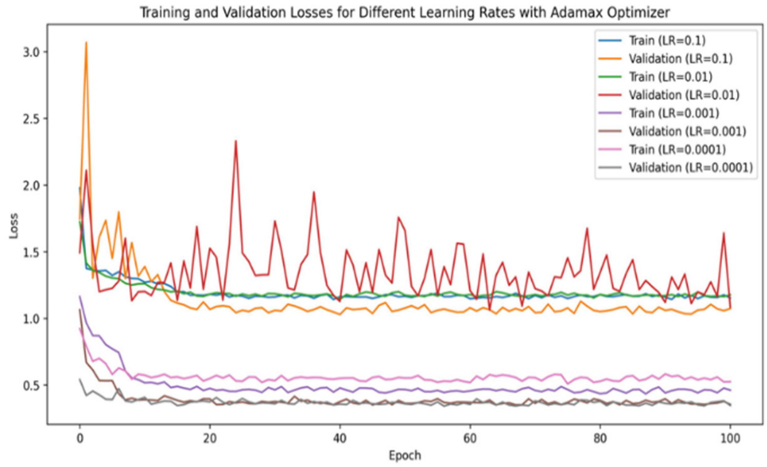

Fig. 4. Training and validation loss of ResNet-18 for various learning rates with Adamax optimizer

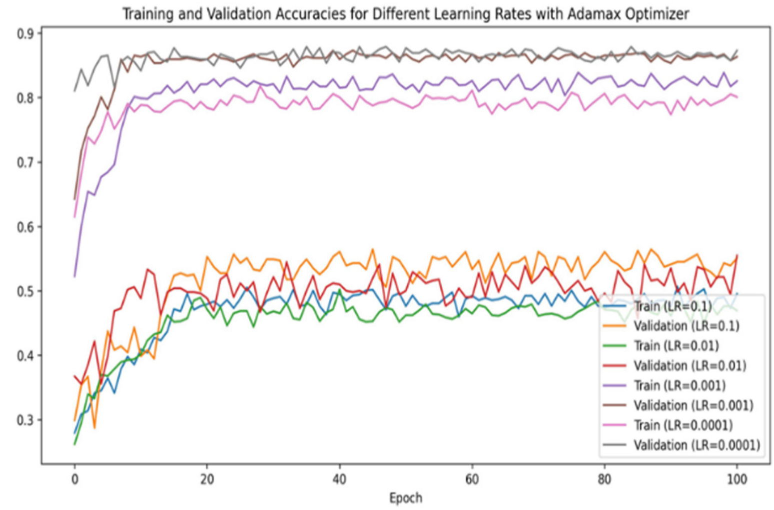

Fig. 5. Training and validation accuracy of ResNet-18 for various learning rates with Adamax optimizer

Fig. 6. Training and validation loss of ResNet-18 for various learning rates with AdamW optimizer

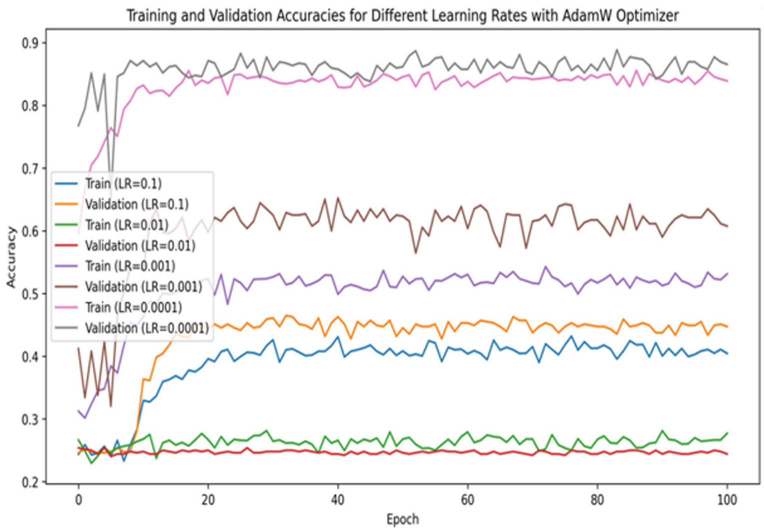

Fig. 7. Training and validation accuracy of ResNet-18 for various learning rates with AdamW optimizer

Figures 5, 7 and 9 depict the training and validation accuracy of ResNet-18 by varying learning rates with Adamax, AdamW and RMSProp optimizer. ResNet-18 achieved good accuracy for AdamW optimizer with the 0.0001 learning rate.

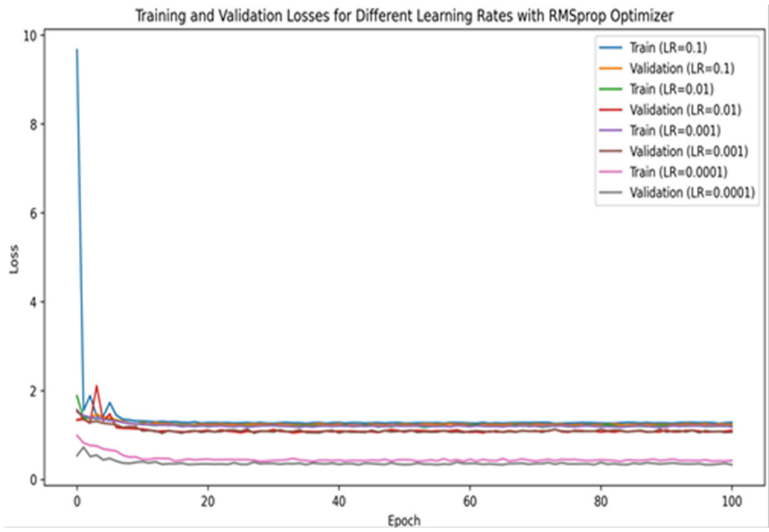

Fig. 8. Training and validation loss of ResNet-18 for various learning rates with RMSProp optimizer

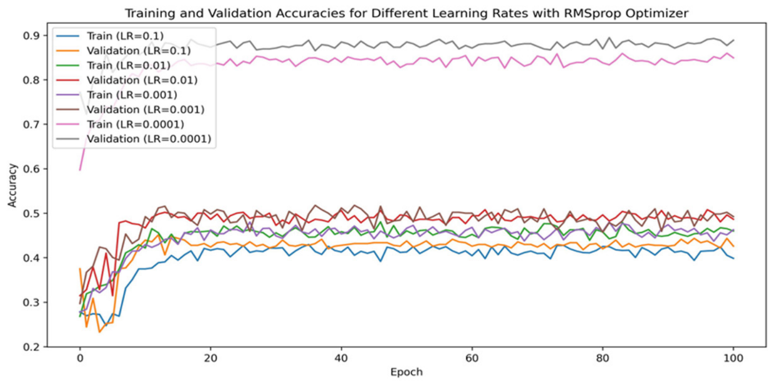

Fig. 9. Training and validation accuracy of ResNet-18 for various learning rates with RMSProp optimizer

Figures 10, 11 and 12 depict confusion matrix of ResNet18 for the different learning rates varying from 0.1 to 0.0001with Adamax, AdamW and RMSProp optimizers.

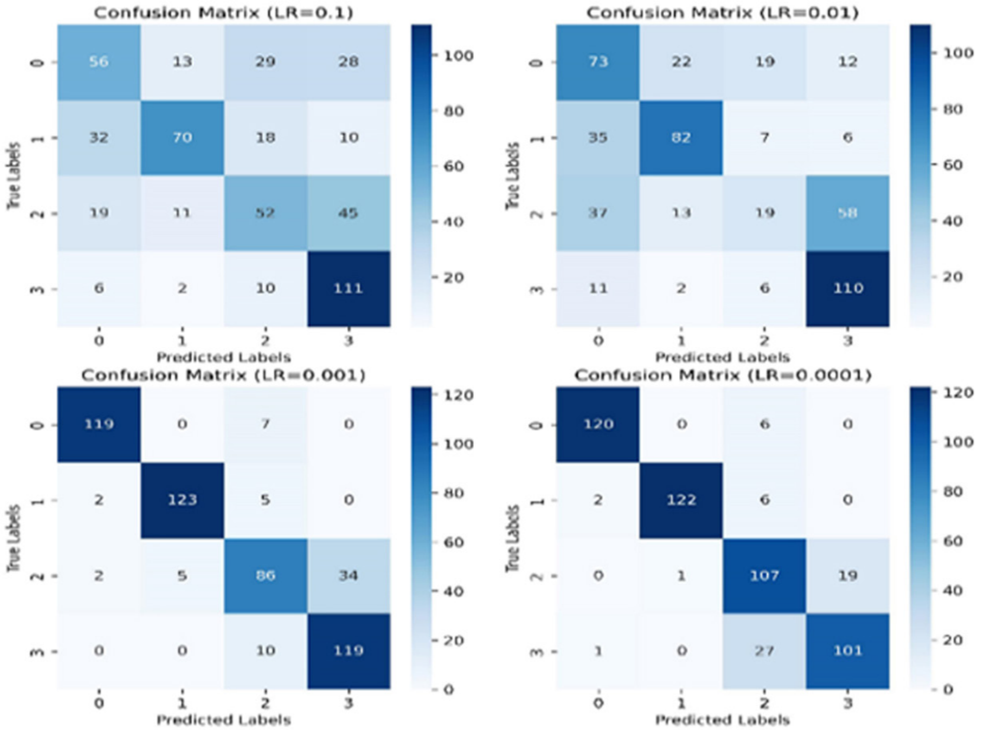

Fig. 10. Confusion matrix for the different learning rates varying from 0.1 to 0.0001 Adamax optimizer

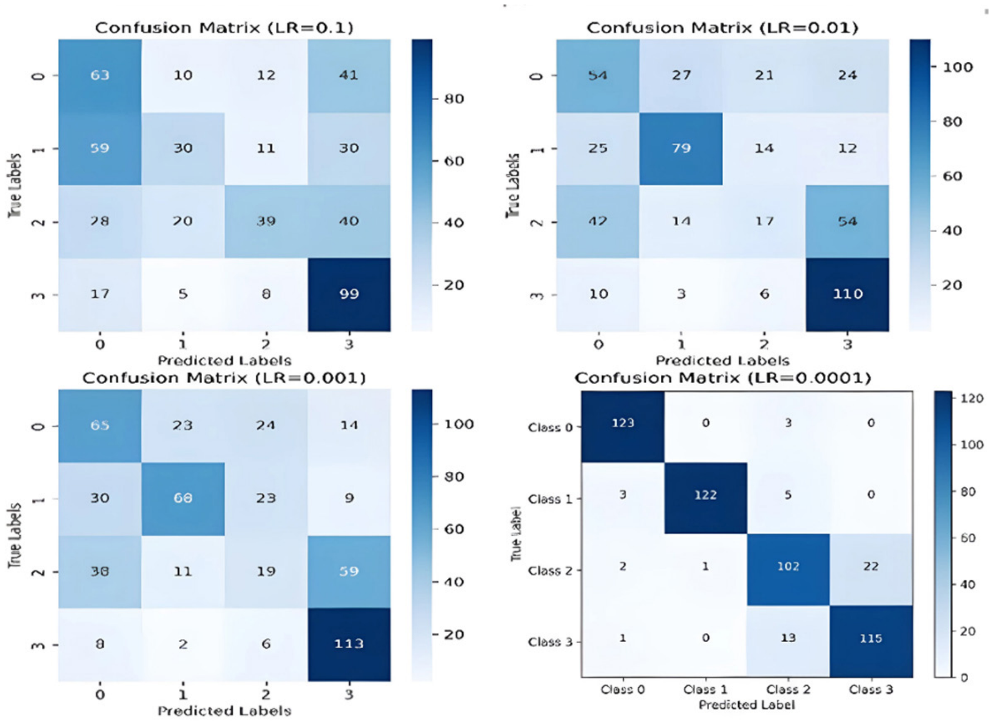

Fig. 11. Confusion matrix for the different learning rates varying from 0.1 to 0.0001 with AdamW optimizer and batch size 4 for 4 class classification

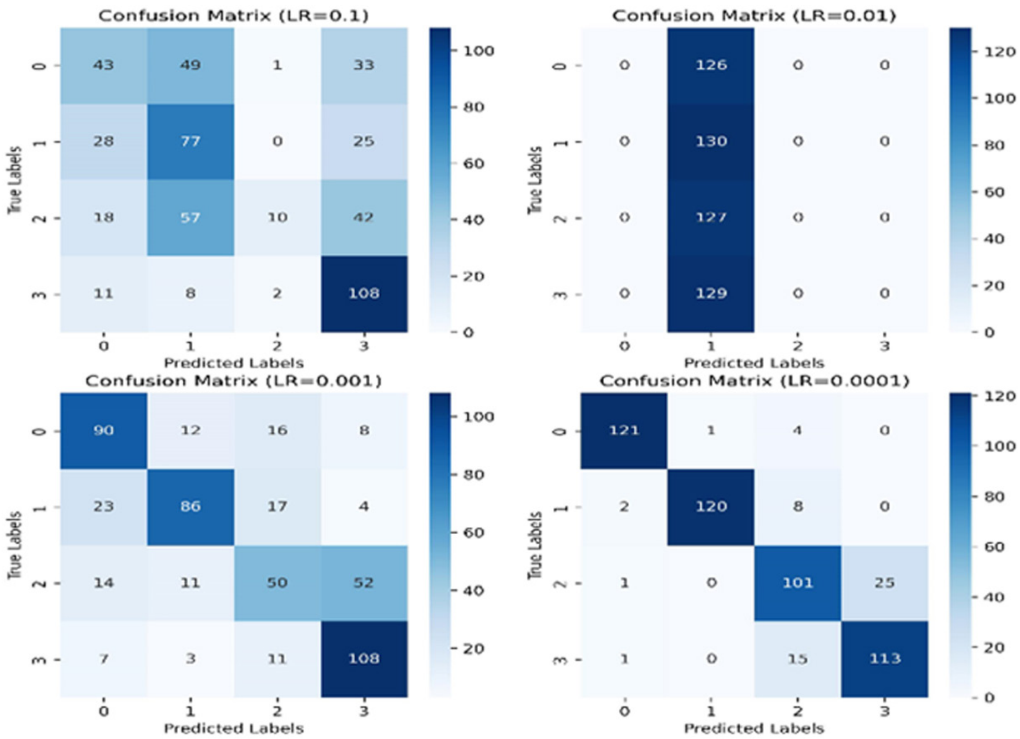

Fig. 12. Confusion matrix for the different learning rates varying from 0.1 to 0.0001 with RMSprop optimizer and batch size 4 for 4 class classification

In Figures 10, 11, and 12, it is evident that the misclassification rates for learning rates 0.1, 0.01, and 0.001 are notably higher when compared to the misclassification rate associated with a learning rate of 0.0001 for the Adamax, AdamW, and RMSprop optimizers. Specifically, when utilizing a learning rate of 0.0001, ResNet-18 misclassifies 62, 54, and 57 instances with the Adamax, AdamW, and RMSprop optimizers, respectively, resulting in misclassification rates of 13.77%, 10.8%, and 12.52%.

The preceding analysis indicates that ResNet-18, when paired with the AdamW optimizer and a learning rate of 0.0001, yields superior performance for the dataset employed in this study. This model is subsequently fine-tuned by varying the number of epochs and batch sizes. ResNet-18 is trained for 50, 100, and 150 epochs, and the results have been analyzed. The findings reveal that the model performs well at epoch 100. There is a slight decrease in training and validation accuracy for epoch 150. Table 8 presents the results of ResNet-18 with the AdamW optimizer, a learning rate of 0.0001, and a batch size of 4 for different epochs.

Table 8. Performance of ResNet-18 with the AdamW optimizer, learning rate of 0.0001, and a batch size of 4 for different epochs

Epochs	Training Accuracy	Training Loss	Validation Accuracy	Validation Loss	Precision	Recall	F1-Score	Training Completion Time
50	83	0.49	86.2	0.35	0.90	0.90	0.92	29m 30s
100	85.1	0.42	88.0	0.28	0.903	0.902	0.902	62m 57s
150	84.9	0.46	88.0	0.31	0.889	0.886	0.887	83m 40s

Further, the effect of the batch size is analyzed by varying the batch size. The results show that the model performs considerably good when batch size 6 with a validation accuracy of 88.8%. Table 9 depicts the performance of the model with the AdamW optimizer, a learning rate of 0.0001, 100 epochs for various batch sizes.

Table 9. Performance of ResNet-18 with the AdamW optimizer, learning rate of 0.0001, and epochs 100 a 4 for different epochs

Batch Size	Training Accuracy	Training Loss	Validation Accuracy	Validation Loss	Precision	Recall	F1-score	Training Completion Time
2	82.3	0.48	0.83	0.39	0.872	0.872	0.872	75m 54s
4	84.9	0.46	88.0	0.31	0.889	0.886	0.887	62m 57s
6	87.0	0.33	88.8	0.35	0.903	0.902	0.90	56m 21s
8	86.5	0.37	87.5	0.37	0.891	0.8910	0.890	50m 28s

This experiment shows that the ResNet-18 model performs well with hyperparameters values shown in Table 10. Figure 13 depicts the confusion matrix obtained by training the model with optimized hyperparameters shown in Table 10. The confusion matrix depicts the misclassification rate of 9.6%.

Table 10. Optimized hyperparameters values

Hyperparameter	Value
Epoch	100
Learning rate	0.0001
Optimizers	AdamW
Batch size	6
Loss function	Categorical cross entropy
Classification	Softmax

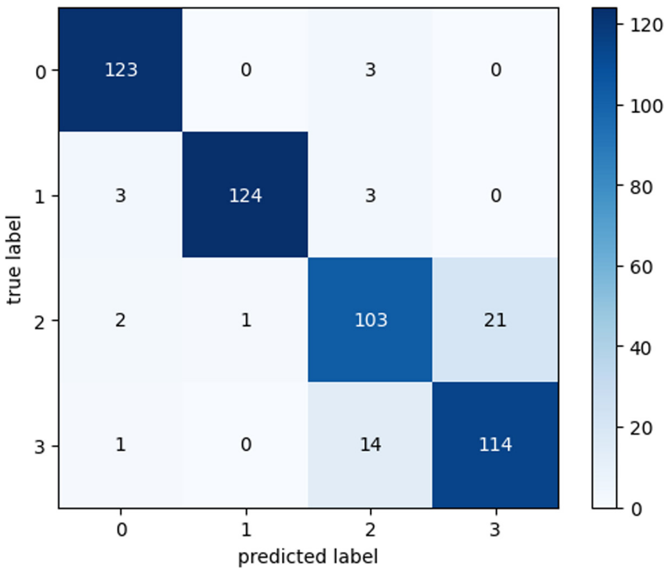

Fig. 13. Confusion matrix of ResNey-18 with optimized parameters

The experimental results show that, ResNet-18 model is effective in the two-class classification task. It achieves impressive performance metrics, with 95%

accuracy, 97.6% F1 score, and 97.6% recall. This suggests that the model can accurately distinguish between malnourished and properly nourished children based on images.

From the above analysis, it can be observed that ResNet-18 model outperforms with optimized hyperparameters shown in Table 10 with validation accuracy of 88.8% for multi-class classification.

5 CONCLUSION AND FUTURE WORK

The primary goal of the research is to create an AI model using deep learning, specifically a ResNet18-based model. This model is designed to classify children into two categories: those suffering from malnutrition and those who are not eating properly, based on images. To achieve this classification, a custom dataset is prepared and used to train the model.

The results of the study indicate that the deep learning model is effective in the two-class classification task. It achieves impressive performance metrics, with 95% accuracy, 97.6% F1 score, and 97.6% recall. This suggests that the model can accurately distinguish between malnourished and properly nourished children based on images.

Additionally, the study broadens the scope of its categorization methodology by incorporating a more intricate situation with four classifications. The model's performance in this configuration is still quite good, with 88.87% accuracy, 90.2% recall, 90.3% precision, and an F1 score of 90.2%.

This method is based on the visual looks of children, though their images have limitation of not prompting the underlying reasons which lead to malnutrition; therefore, this work has opportunity of improving by incorporating additional suitable information on child health, such as parental background, demographic details, and minimal pathological records. This model contributes to reducing initial examination of the child with the AI model that is suitable for deprived geographic regions. In future, this work aims to prepare a comprehensive real-world child image. The proposed model helps in examination taking surveys for identifying initial findings.

This work can be further refined by enhancing malnutrition detection and risk prediction. To achieve this, additional data related to micronutrients and chronic diseases will be collected. Early detection of malnutrition recovery strategies can be achieved by employing deep learning models on personalized data.

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