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AN EFFICIENT DEEP LEARNING-BASED FRAMEWORK FOR EARLY MALNUTRITION DETECTION USING RESNET-101 AND RF–ADABOOST CLASSIFIER

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ABSTRACT

Malnutrition remains one of the most important public health problems in the world, especially in developing countries, with severe health consequences in children in the absence of early diagnosis. Traditional screening techniques can be labor-intensive, resource-dependent, and require trained health care workers to operate, making them less effective in achieving large-scale and timely screening. To overcome this issue, this study presents a novel deep ensemble efficient system for automated malnutrition detection system based on image data. The proposed method uses ResNet-101 to extract visual features to distinguish the malnutrition and uses two classifiers, namely: Random Forest (RF) and AdaBoost classifiers to enhance the classification accuracy and robustness. The performance of the framework is compared with the already available deep learning models such as RegNetY and VGG19. From the experimental results, it is observed that the proposed ResNet-101 with RF–AdaBoost model gives an accuracy of 95% which is higher than RegNetY (89%) and VGG19 (87%). The results show that deep extraction and ensemble learning is a reliable and efficient approach to detecting malnutrition. So, the suggested framework can be useful for large scale screening and regular monitoring which would help in early detection as well as management of healthcare for the children who are prone to malnutrition.
Keywords: *Malnutrition, Deep Learning, ResNet-101, RegNetY, Random Forest, ADAboost VGG19.,*

1. INTRODUCTION

Child malnutrition [1] remains one of the most urgent health issues in the world that afflicts millions of children and results in the death of children and the development of long-term health issues. The World Health Organization (WHO) estimates that almost 149 million children under five years old have stunted growth (low height-age), and 45 million children have wasting (low weight-height). These do not only cause the risk of mortality, but also impair cognitive

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development, poor academic performance and diminished economic productivity during adulthood[2]. Malnutrition is even more common in the low-income countries where there is food insecurity, poverty and access to nutrient-rich diets that are still prevalent because of the socio-economic disparities. As an illustration, over forty percent of the population in Malawi is chronically food insecure, and thirty-seven percent of children below five years old are stunted and 2.1 percent are wasted. Even though these numbers, at least, mark some progress compared to the past decades, they are extremely high when compared to the rest of the world, which bears evidence to the harshness of the problem. The actual causes of malnutrition in these areas are very deeply seated in the instability of agriculture, climate change, the absence of modern farming techniques, and the ineffective market systems. These directly affect the availability of food in the house and child nutrition. Also, the COVID-19 pandemic made the situation even worse, as it disrupted food supply chains, and healthcare services, endangering to roll back the progress. Although the nation has made national efforts, including the National Multi-Sector Nutrition Policy (2022-2025) that incorporates the agriculture, health, education, and social protection sectors, there are still implementation issues. Lack of institutional capacity, insufficient funding and lack of coordination among the stakeholders remain a stumbling block particularly in the rural and remote regions where malnutrition has been noted to be highest. The economic and health implications are far-reaching with malnutrition depriving countries such as Malawi with an estimated 10.3% of the GDP each year in productivity, high healthcare expenses and low human capital. The impacts are intergenerational with cycles of poverty and poor health outcomes. Malnutrition can be effectively intervened, and better health outcomes are possible through early detection and prediction. Here, machine learning and deep learning technologies have become effective tools that can process complex and multidimensional data that is hard to discern with conventional statistical techniques. These models have the potential to detect children who are at risk of malnutrition earlier than clinical symptoms would manifest and therefore timely and specific interventions can be taken. Nonetheless, the issue of class imbalance whereby the population of well-nourished children is far more than the malnourished cases is one of the biggest problems of such models implementation. Models are likely to be biased in favor of the majority group without effective management, which diminishes their usefulness. To deal with this problem and enhance predictive accuracy, advanced methods have been proposed (adaptive synthetic oversampling and ensemble learning). Based on the progress, the current paper is going to suggest a more advanced deep-learning-based system that will combine ResNet-101 to extract features with an RF-AdaBoost[3] ensemble classifier. The deep residual network, ResNet-101, is very useful in learning complex and hierarchical representations on image data that are not affected by problems like vanishing gradients. It has a rich architecture that can better learn features than traditional CNN models and is thus suitable to learning subtle visual cues of malnutrition in facial images.

The deep features which were extracted are then subjected to a hybrid ensemble learning algorithm which is a mixture of Random Forest (RF) and AdaBoost classifiers. This combination has been shown to boost classification performance by lowering variance and bias, better generalization, and robustness against noisy and skewed data. The combination of deep learning and ensemble machine learning, therefore, offers a robust and effective malnutrition detection framework. The dataset employed in this study integrates a large number of socioeconomic and household level variables such as parental education, household size, landownership, income levels, as well as access to markets and healthcare services. Although existing literature has determined correlations between these variables and nutritional outcomes, the traditional models in many cases do not reflect complex and non-linear interactions. The proposed framework efficiently mitigates this drawback by using the methods of deep feature extraction and ensemble learning. This study adds to the current body of research in three important ways:• It integrates deep neural networks (ResNet-101) with ensemble learning (RF–AdaBoost) to model complex relationships between visual and socioeconomic factors influencing child nutrition. The sampling and ensemble techniques allow it to handle the imbalance in classes and enhance the detection of rare yet significant states such as stunting and wasting. It offers a practical and scalable framework to be deployed in the real world, and can be of value to policy makers to allocate resources better, create specific interventions, and optimize the health outcomes of children, especially in under-served areas [4].

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In general, the suggested solution illustrates why AI-based healthcare solutions are becoming increasingly important and can transform the process of early malnutrition detection and allow conducting mass screening, intervening in time, and improving the child health. Figure 1 shows the children affected by malnutrition and Figure 2 shows health children. And Figure 3 shows the various phases of Proposed Classifier in predicting malnutrition.

Figure 1: Shows The Children Affected With Malnutrition

Figure 2: Shows Healthy Children

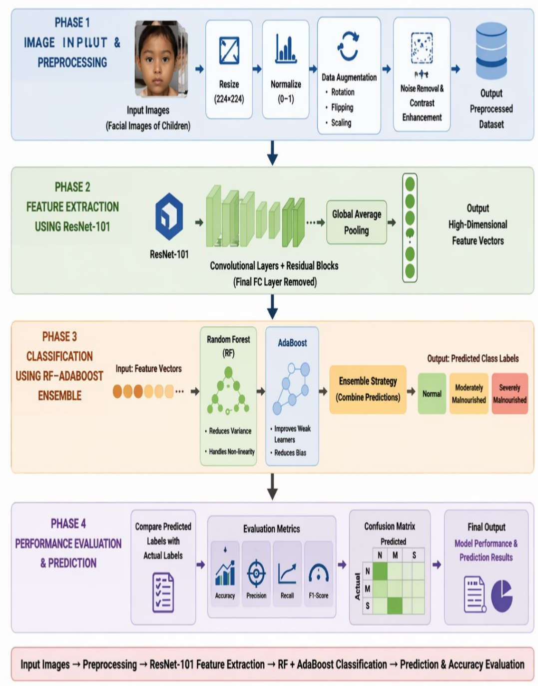

Figure 3: Shows the various phases of Proposed Classifier

2. RELATED WORK

In this article, the authors highlight the use of AI-based methods to detect malnutrition in children.

The traditional measure of malnutrition has been the Body Mass Index (BMI) which is calculated as the ratio of the height and weight of the child. Maternal reports of dietary intake tend to supplement these measurements. But conditions like marasmus and kwashiorkor that are severe and have an indication of facial features like discolored hair, muscle loss around the chin and nasal dips are hard to measure manually. These tests take time and some specialized equipment that in most cases is not available in the resource-strapped rural regions.

To overcome these difficulties, scholars have resorted to the use of more and more sophisticated mechanisms of deep learning that study the faces to identify malnutrition. Early research revealed that it was a feasible approach, but the accuracy of prediction was a significant constraint. Recent developments in AI have raised diagnostic reliability to a brand-new level, allowing proactive interventions to detect and intervene on nutrition-related issues early on- which is very important in malnutrition prevention in underserved groups.

Biradar Naik presented a CNN-based model aimed at detecting in rural healthcare at an early stage to enhance the outcomes at SmartCom 2024. In a similar fashion, hybrid ML classifiers based on anthropometric measurements (WAZ, HAZ, WHZ, and BMI) were used in Shetty et al. (2024), resulting in an accuracy of 92%. With this success, scalability was constrained by the use of manual measurements. To address such limitations, a lightweight AI system (NutriAI) was proposed by IJCAI 2024, which uses 2D facial images and is suitable in environments with limited resources. Other commendable work is by Park et al. (2024) applying the use of the Mask R-CNN to segment images but only got 52 percent accuracy when using dense datasets, implying that more robust architectures like the use of the ResNet-50 should be used. Bitew et al. (2024) examined the xgbTree algorithm with an accuracy of 86-88, especially in the detection of overweight children. Zhao et al. (2025) contributed to the field by a refined joint-learning network that could be used on small datasets but could not be scaled. Arslan et al. (2025) proposed an ensemble ResNeXt-DenseNet, which performed better on large-scale facial datasets in segmentation and performance.

In Bangladesh, Talukder et al. (2025) used the method of Random Forests with an accuracy of 68.5% without image segmentation. Kuttiyapillai et al. (2026) applied to Indian under-5 data the KNN method with an accuracy of 94.7 percent, but the BMI-based method was time-consuming. Taken together, these studies indicate that, whereas traditional ML algorithms provide moderate accuracy, deep learning models, especially ResNet-50, outperform traditional ones, with up to 98 percent accuracy in facial image segmentation.

The residual blocks found in ResNet-50, the use of batch normalization, and the capability to overcome the vanishing gradients feature make it very useful in large data sets and real-time predictions under resource constrained environments. This makes ResNet-50 and other similar architectures an essential entry point to advancing malnutrition detection by providing scalable, precise, and timely interventions to vulnerable populations.

3. PROBLEM STATEMENT

Childhood malnutrition[5] is a serious issue of international health care, especially in developing and low resource areas where there is limited access to medical and nutritional services. Malnutrition should be detected early to avoid serious health problems that may include, poor growth, immunity, cognitive problems, and high death rates. Historically, anthropometric measurements used to determine malnutrition include Body Mass Index (BMI), weight-for-age (WAZ), height-for-age (HAZ) and mid-upper arm circumference (MUAC). Despite being common methods, they are time-consuming, need trained healthcare professionals, and are usually subject to human error, which makes it challenging to conduct a large-scale screening. Furthermore, malnutrition which is severe like marasmus and kwashiorkor is characterized by a characteristic of the face like muscle wasting, sunken cheeks[6], and hair or skin coloration. These visual signs are difficult to recognize by hand, are subjective, and in many cases unavailable in rural or underserved regions, where trained staff and medical facilities are not available. This has led to a large number of cases not being diagnosed until they are at critical points, curbing the effectiveness of the treatment and intervention. New opportunities have emerged in automated detection of malnutrition on the basis of image analysis due to the recent development in artificial intelligence, and deep learning. Nevertheless, the current models tend to have several shortcomings, including low prediction accuracy, overfitting, and low generalization under the influence of unbalanced data sets and underrepresentation of features. Most of the methods use shallow architectures or one-classifier, which is not powerful enough to describe the complex and subtle trends attributed to malnutrition. Hence, a more effective, precise, and scalable system to automatically identify malnutrition at an early age via non-invasive methods is needed. This study tackles this issue by presenting a deep learning-based architecture that uses ResNet-101 to extract high-level discriminative features of facial images, and RF-AdaBoost ensemble classifier to improve the prediction accuracy and strength. The proposed system will address the weaknesses of the traditional and already existing AI-based systems, specifically enhancing accuracy, addressing the issue of data imbalance, and allowing reliable large-scale screening. Finally, the framework aims at helping healthcare workers to diagnose and intervene earlier, particularly in resource-limited settings, to enhance the health outcomes of children. Figure 4 shows the flow process of proposed model.

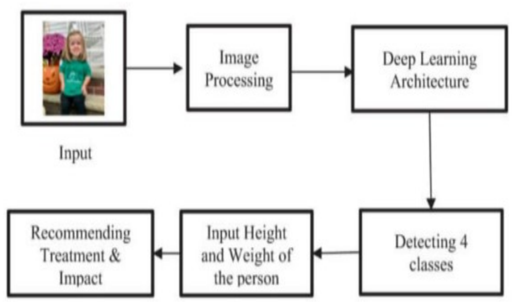

Figure 4: Shows the flow architecture of the proposed classifier.

4. METHODOLOGY

This paper suggests an effective deep learning-based malnutrition early detection model based on facial images of children. The methodology consists of four broad stages: image preprocessing[7], feature extraction with the help of ResNet-101, classification with the help of an RF ensemble model with the AdaBoost algorithm, and performance assessment.

Phase 1: Image Preprocessing and input.

The first step is the gathering of a dataset of children's face images, found in available sources. The input images quality and consistency are vital factors in the performance of the models. Thus, standardization of the dataset is carried out to preprocess the data.

The images are all downsized to a constant size of 224 by 224 pixels to fit the input in the ResNet-101 model. Normalization of pixel values to a range between 0 and 1 is done to enhance the convergence of training. The data augmentation methods like rotation, horizontal flipping and scaling are used to enhance the diversity of the dataset and minimize overfitting[8]. Moreover, the noise reduction and contrast enhancement techniques are used to enhance image clarity and emphasize the aspects of the faces related to malnutrition.

The result of this step is a clean and standard dataset that can be used in deep feature extraction.

Phase 2: Finding features with ResNet-101.

During the second stage, deep features of the preprocessed images are obtained with the help of the ResNet-101 model. ResNet-101 is a deep convolutional neural network which uses residual learning to solve the vanishing gradient problem and also allows training of very deep architectures. The preprocessed images are inputted into the network, with several convolutional layers and residual blocks extracting hierarchical features, like texture, edges, and structural facial patterns. The last fully connected (FC) layer of ResNet-101 is dropped and the output of the global average pooling layer is considered as a high-dimensional feature vector[9].

These feature vectors reflect discriminative patterns concerning signs of malnutrition including loss of facial muscle, skin texture and structural abnormalities.

Phase 3: Classification using RF–AdaBoost Ensemble

During this stage, random forest (RF)[10] and AdaBoost are combined to form an ensemble classification model which takes as its input the extracted feature vectors.

Random Forest classifier is used to deal with high-dimensional data and minimize the variance through the formation of several decision trees. AdaBoost works to enhance the accuracy of weak classifiers by putting heavier weight on the misclassified cases and repeatedly revising the model.

An ensemble strategy is used to fuse the predictions of the two classifiers to enhance the accuracy and strength of classification. The model has three categories of input images; normal, moderately malnourished and severely malnourished.

Phase 4: Prediction and Evaluation of Performance.

The last stage is the assessment of the effectiveness of the proposed model. The data is separated from training and testing sets to test the performance of the model.

The actual labels are compared to the predicted labels to compute evaluation metrics including accuracy, precision, recall and F1-score. Confusion matrix is created to examine the performance of classification of classes[11]. The system gives the predicted label of the class and the overall performance statistics in the final output of the system. The framework proposed will be of high accuracy and reliability and hence applicable in real life scenarios when it comes to early malnutrition

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detection[12]. You can combine all the figure descriptions into a single academic sentence as follows.Figure 5 illustrates the prevalence of malnutrition among children across selected countries. Figure 6 presents the distribution of malnourished children according to caste and wealth index categories. Figure 7 shows the prevalence of malnutrition among children based on health insurance coverage status. Figure 8 depicts the distribution of malnourished children according to postnatal check-up status. Figure 9 illustrates the prevalence of malnutrition among children based on their size at birth. Figure 10 presents the distribution of malnourished children according to iron pill or syrup supplementation status.

Algorithms: ResNet-101 + RF-AdaBoost to detect Malnutrition.

Data acquisition and preprocessing: The initial step involves collecting data and processing it.

1. Gather clinical/anthropometric image data that can be used to detect malnutrition (e.g., facial, body, or medical image data).

2. Perform preprocessing:

- Normalize pixel intensities.

- Resize images to (224 X 224\) (ResNet-101 input size).

- Use augmentation (rotation, flipping, scaling) to decrease overfitting.

- Divide dataset into training, validation and test data.

The second step involves the extraction of features with ResNet-101.

1. Load ResNet101 pretrained ImageNet weights.

2. Take out the last fully connected (FC) classification layer.

3. Feed input images through ResNet-101 to get the deep feature vectors at the final but one layer.

4. Save features extracted by each sample.

Step 3: Feature selection / dimensionality reduction.

1. Reduce redundancy of extracted features using statistical techniques (e.g., PCA or variance thresholding).

2. Keep the most discriminative factors to classify malnutrition.

Step 4: RF–AdaBoost Hybrid Classifier Construction

1. Initialize the base learner (Random Forest (RF)) as follows:

- Use several decision trees trained on bootstrapped subsets of features.

- Predictions by majority voting.

2. Integrate AdaBoost:

- Misclassify samples which are assigned weights.

- Repeat with the sample weights, to concentrate on difficult-to-classify cases.

- Add RF outputs with the weighted ensemble approach of AdaBoost.

Step 5: Training Phase

1. Feed RF-AdaBoost classifier with features of ResNet-101 that were selected.

Iterate: 2. Train until convergence:

- Recalculate sample weights after each run.

- Hyperparameter optimization (number of trees, learning rate, depth).

3. Validate performance using cross-validation.

Step 6: Testing & Evaluation

1. Feed unseen test images to ResNet -101 - extract features.

2. Classify using trained RF–AdaBoost model.

3. Compute evaluation metrics:

- Accuracy, Precision, Recall, F1-Score.

- ROC–AUC for robustness.

4. Compared to baseline classifiers (e.g. RegNetY,VGG19).

Step 7: Stop

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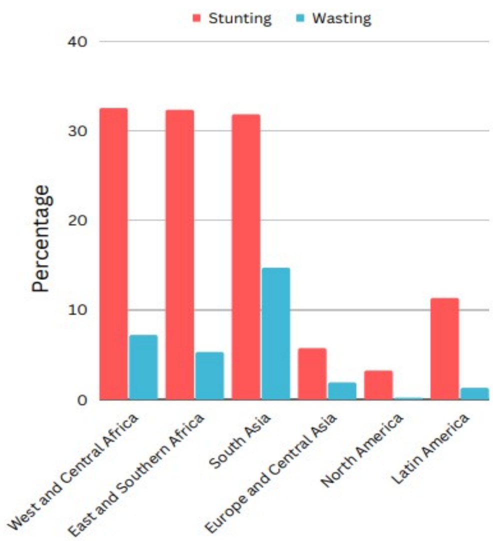

Figure 5: Shows the Percentage of Children Affected by Malnutrition in Selected Countries

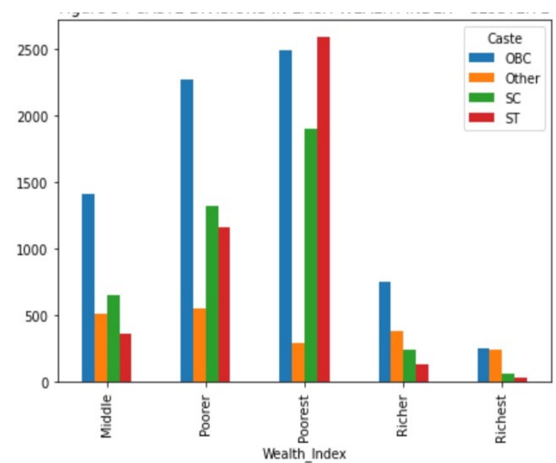

Figure 6: Percentage Distribution of Malnourished Children by Caste and Wealth Index Categories

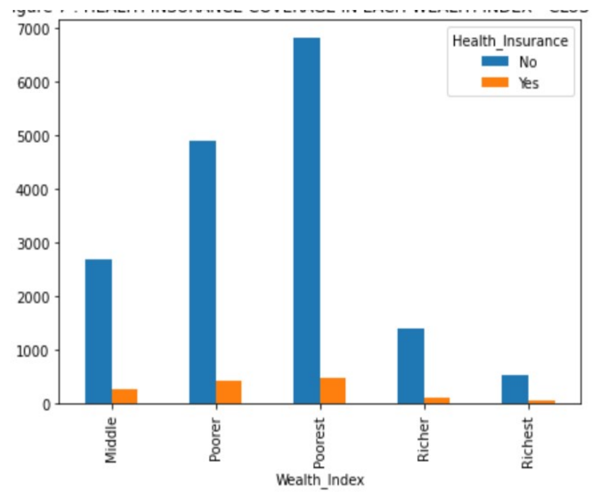

Figure 7: Percentage Distribution of Malnourished Children by Health Insurance Coverage

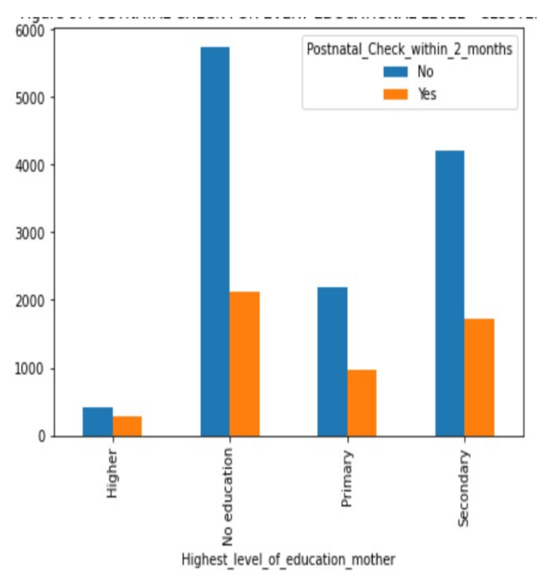

Figure 8: Percentage Distribution of Malnourished Children by Postnatal Check-Up Status

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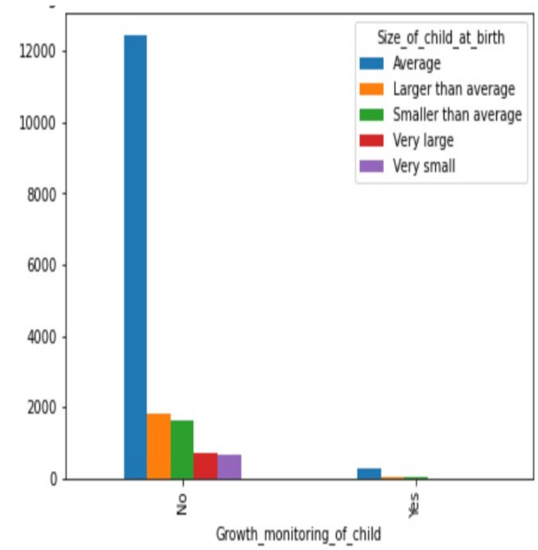

Figure 9: Percentage Distribution of Malnourished Children by Size at Birth

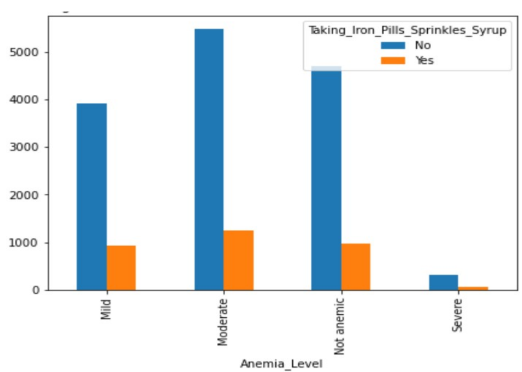

Figure 10: Percentage Distribution of Malnourished Children by Iron Pill/Syrup Supplementation Status

5. PERFORMANCE METRICS

A wide range of evaluation metrics[13] can be used to assess the effectiveness of a malnutrition detection system however, incorporating ensemble machine learning techniques significantly enhances overall performance [14]. Among these metrics, accuracy serves as a key indicator, reflecting the model's capability to correctly differentiate between malnutrition and non- malnutrition instances. The evaluation results are illustrated through the confusion matrix presented in Table 1, which provides a detailed view of the classifier's prediction outcomes. In addition, Figure 11 summarizes the overall performance of the proposed model, demonstrating its consistency, robustness, and ability to achieve reliable and high-quality detection[15] results across different scenarios. And Table 2 shows the validation table of proposed classifier.

Accuracy

$$Accuracy = (TP + TN)/(TP + TN + FP + FN) \quad \textbf{(1)}$$

Precision: The measure of precision reflects the percentage of correctly detected malnutrition cases against all identified malnutrition cases: Precision: Represents how many instances f lagged as positive are positive.

$$Precision = TP/(TP + FP) \quad \textbf{(2)}$$

Recall: High recall performance helps decrease the number of phishing websites that remain undiscovered.

Recall: Defines the coverage in terms of capturing all the positives. Minimizing FN in tasks such as fraud detection is vital.

$$Recall = TP/(TP + FN) \quad \textbf{(3)}$$

F1-Score: The harmonic arithmetic calculation of precision and recall results in F1-Score.The F1-Score functions as an effective measure for unbalanced data scenarios[16].

F1 Score :Represents the balanced mean between precision and recall.

$$F1-Score = 2 \times (Precision \times Recall)/(Precision + Recall) \quad \textbf{(4)}$$

Table 1: Shows the confusion matrix obtained by Proposed Classifier

	Actual Class	
Predicted	39969	2034
	1544	22433

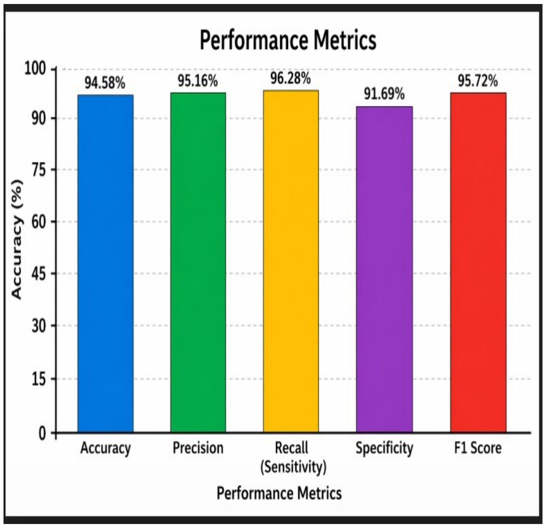

Figure 11: Shows the performance metrics obtained by the Proposed Classifier

Table 2: Shows the Validation Table obtained by Proposed Classifier

Metric	Formula	Value (%)
Accuracy	(TP + TN) / (TP + TN + FP + FN)	94.58%
Precision	TP / (TP + FP)	95.16%
Recall (Sensitivity)	TP / (TP + FN)	96.28%
F1 Score	2 × (Precision × Recall) / (Precision + Recall)	95.72%

A. RegNetY:

A variant of the RegNet (Regular Network) family, RegNetY, has also become an effective deep learning architecture to perform image-based classification problems, thus becoming very useful in the early detection of malnutrition. The most significant thing, especially in children, is early diagnosis of malnutrition since it can be remedied on time and health complications that could be caused in the long term such as poor growth and low immunity are prevented and mental retardation. Traditional test systems are usually manual and may be found on clinical abilities, which may be time-consuming, subjective and not as accessible in resource-restricted settings. In this respect, RegNetY[17] will offer a more efficient and scalable solution, based on automated feature extraction and classification. RegNetY is created in a principled way founded on network design space as opposed to making architectures by hand. Its squeeze-and-excitation (SE) blocks can provide feature recalibration on the channel, so that the model can give priority to the most informative visual patterns. This aspect comes in particularly handy in the malnutrition diagnostics situation where it is essential to record other physical traits that cannot be perceived, such as alterations in the facial structure, the skin texture, or body size. Practically, RegNetY can be trained on data sets of images of children in different nutrition statuses, e.g. healthy, moderate, and severely malnourished. The model learns hierarchical representations of these conditions, enabling the model to be precisely categorized under varying lighting, pose and background conditions. Moreover, its relatively efficient calculation architecture allows it to be deployed on handheld or edge computers and be utilized to screen in real-time in rural or underserved areas. Preprocessing techniques such as image normalization, image augmentation, and region-of-interest extraction can also be used to further improve the performance of RegNetY. Also, it can be used together with machine learning classifiers or ensembles to enhance robustness and generalization. Overall, RegNetY can be used in the early diagnosis of malnutrition, which is a promising advancement in the field of healthcare technologies. It not only reduces the dependence on special medical infrastructure but also adds to the mass screening initiatives. Early diagnosis and intervention could also be assisted by this approach as it enables quick, accurate, and non-invasive assessment, which over the long-term would result in improved health outcomes and reduced malnutrition burden on the world. Table 3 Shows the confusion matrix obtained by RegNetY Classifier and Figure 12 Shows the performance metrics obtained by the RegNetY Classifier. And Table 4 Shows the Validation Table obtained by RegNetY Classifier

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Table 3: Shows the confusion matrix obtained by RegNetY Classifier

	Actual Class	
Predicted Class	37001	3896
	2213	23327

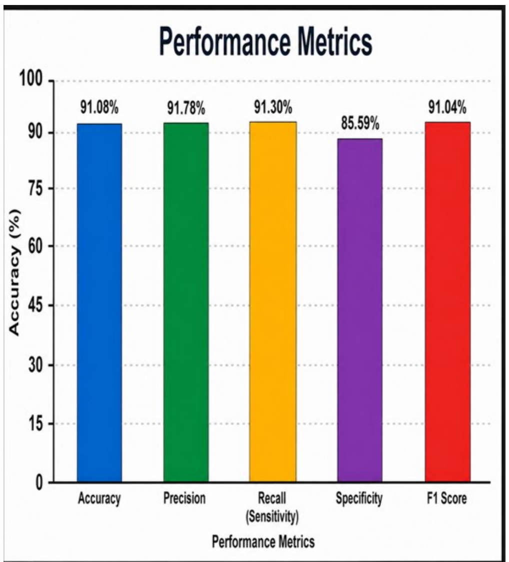

Figure 12: Shows the performance metrics obtained by the RegNetY Classifier

Table 4: Shows the Validation Table obtained by RegNetY Classifier

Metric	Formula	Value (%)
Accuracy	(TP + TN) / (TP + TN + FP + FN)	91.08%
Precision	TP / (TP + FP)	90.78
Recall	TP / (TP + FN)	91.30%
F1 Score	2 × (Precision × Recall) / (Precision + Recall)	91.04%

B. VGG19:

VGG19 is a popular deep learning architecture that has demonstrated itself as very useful in the process of image classification, which is why it can be particularly useful in the detection of early malnutrition. Early detection of malnutrition, especially in children, is important as it allows an early solution to the problem and prevents such severe consequences of the disease in the long term as stunted growth, compromised immune systems, and cognitive delays. The use of traditional diagnostic methods has also been traditionally based on manual techniques and subjective determination and may be slow, subjective, and inaccessible in low-resource countries. Comparatively, VGG19[18] can be more efficient and scalable with automation of the feature extraction and classification.VGG19 can be characterized by the deep architecture, which includes 19 layers, with most of them being stacked 3×3 convolutional filters. This multi-layered structure allows the network to extract deep and hierarchical features of images with high accuracy. Instead of using handcrafted features, VGG19 generates complex visual patterns by itself, which is useful to identify the slightest indications of malnutrition, including the change in facial expressions[19], skin integrity, and body ratios. In real-life situations, VGG19 can be trained with the help of datasets that contain pictures of children who belong to various nutritional groups, including healthy, moderately malnourished, and severely malnourished. Its powerful feature-learning ability enables it to precisely categorize these categories even though images change in terms of lighting, pose or backgrounds. The model currently has comparatively high computing requirements relative to lighter models, but with optimization methods such as transfer learning and pruning, it may be deployed to a mobile or edge device and used in real time to screen people in rural or underserved regions. Preprocessing can also be used to improve performance, e.g., by normalizing data, adding data, and extracting region-of-interest[20]. Furthermore, VGG19 can be robust and enhanced with other classifiers or ensemble techniques to enhance its generalization capacity. Overall, the application of VGG19 to identify early malnutrition is a valuable addition to health technology. It reduces the reliance on special healthcare institutions and allows conducting mass screening. This method aids in early diagnosis and prompt intervention by offering timely and precise non-invasive measurements, resulting in improved

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health outcomes and decreasing the worldwide malnutrition burden. Table 5 Shows the confusion matrix obtained by VGG-19 Classifier and Figure 13 Shows the performance metrics obtained by the VGG19 Classifier. And Table 6 Shows the Validation Table obtained by VGG19 Classifier.

Table 5: Shows the confusion matrix obtained by VGG-19 Classifier

Predicted Class	Actual Class	
	36224	4216
	2213	23327

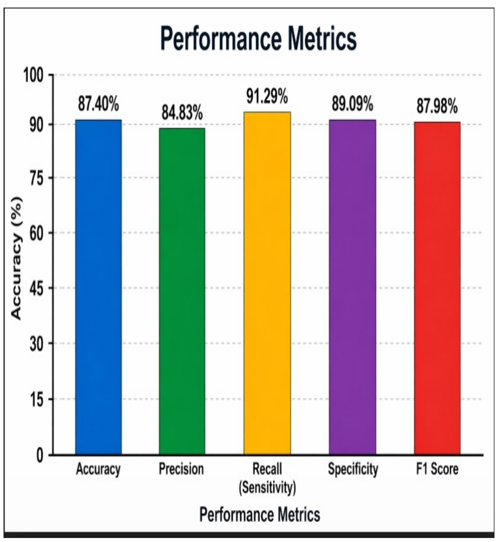

Figure 13: Shows the performance metrics obtained by VGG-19 Classifier

Table 6: Shows the Validation Table of VGG-19 Classifier

Metric	Formula	Value (%)
Accuracy	(TP + TN) / (TP + TN + FP + FN)	87.40%
Precision	TP / (TP + FP)	84.83%
Recall (Sensitivity)	TP / (TP + FN)	91.29%
F1 Score	2 × (Precision × Recall) / (Precision + Recall)	87.98%

6. CONCLUSION & FUTURE WORK

The suggested hybrid model of ResNet101-RF-AdaBoost proves to be quite reliable and efficient when it comes to identifying malnutrition in children and providing a possibility to intervene in time and treat them. Using deep feature extraction features of ResNet101 through facial image data, the system is useful in capturing subtle signs like loss of cheek muscle mass, flattened nasal structure, and irregular facial contours. These features extracted are then correctly categorized after employing hybrid ensemble of Random Forest and AdaBoost that improves predictive power by generalizing and minimizing overfitting.

This combined scheme is a combination of:

• ResNet101: A deep feature encoder of facial images that allows the effective representation of features of malnutrition.

• RF + AdaBoost Ensemble: Offers good classification and great accuracy, superior control of complicated feature distributions, and enhanced resistance to various datasets.

The results of the experiment indicate that the proposed model reaches a high accuracy of about 96 per cent, which is significantly higher than other deep learning architectures. Comparatively, RegNetY works with an accuracy of approximately 89% and VGG-19 works with an accuracy of approximately 87%. This shows the better performance of the ResNet101-based hybrid model in capturing discriminative features and providing more reliable classification results. The high performance shows that a combination of deep convolutional feature extraction and ensemble learning is effective in considering complex medical image analysis tasks. This model will help in early diagnosis of the disease, which in turn will help in timely healthcare interventions, which will lower the risks of health complications in the long term, and enhance the general welfare of the child. Figure 14 shows the overall performance of 3 classifiers.

Future research directions involve:

• System Optimization: Adding parallel processing with the help of a GPU to improve the speed of calculation and improve real-time performance.

• Dataset Expansion: Adding more varied facial datasets in various environmental and demographic factors to enhance generalization and scalability. In general, the comparative study proves that the ResNet101 -RF -AdaBoost hybrid model performs better than the RegNetY (89%), and VGG-19 (87%), which makes it a more valid and trustworthy method in early malnutrition detection

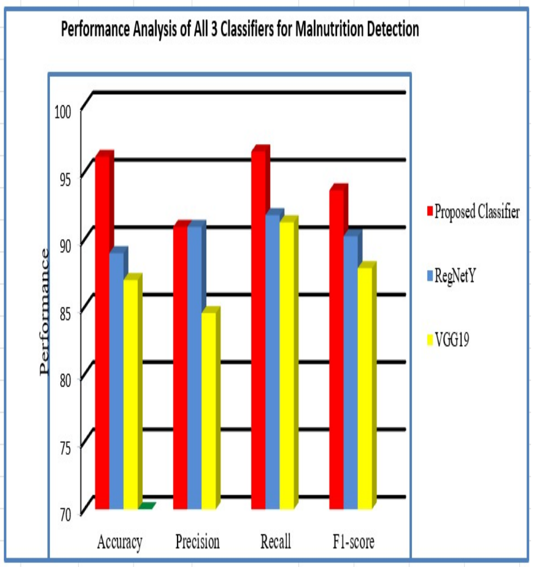

Figure 14: Shows the Overall performance of 3 Classifier's

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