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Cuckoo Search-Optimized Residual Networks for Identification of Diabetic Foot Ulcers

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***Abstract*— The identification of Diabetic foot ulcers (DFUs) is a complicated medical diagnosis and treatment that is tough to deal with, so it needs to be very accurate and effective. The purpose of the study is to show the way to better recognize the DFUs through the use of Cuckoo Search-Optimized Residual Networks (CS-ResNet). The CSO's contribution to the network allows it to adapt to the learning process, thus enhancing feature extraction and classification performance. The approach is based on the optimization strategy, which is soft tuning of the deep learning model's parameters that, in turn, makes it more efficient in finding the right solutions and in achieving the best results in the identification of DFUs. The residual network framework is the cause of gradient vanishing issues because it provides a deep enough representation learning for complex ulcer patterns. The said model contains a feature selection mechanism that constantly improves the accuracy of detection through the selection of optimized features. The hybrid approach that includes both Cuckoo Search and Cuckoo Search Optimization strengthens model stability, which in turn makes medical imaging real-world applications more confirmable. The pilot study, which aimed to track the predicted enhanced DFU identification with the CS-ResNet model, shows the high efficacy of the method.**

Keywords*— *Cuckoo Search model, Residual type of Networks, Diabetic Foot Ulcers disorder, supervisor Learning, related Feature Extraction, Medical based Imaging, Adaptive Optimization process, Classification type, Convergence Improvise model, diseases Pattern Recognition.

I. INTRODUCTION

People with foot ulcers due to diabetic rates are at great risk of health complications, especially those with diabetes. Their hospital admissions account for the majority of patients with diabetic foot ulcers, and they may ultimately have to undergo limb amputations if they are not recognized and treated at an early stage. In the medical field, inflammation in the skin area is known as a diabetic foot ulcer. Some complications that occur can be severe to the extent of requiring a limb to be amputated or death. Hence, early and correct identification of diabetic foot ulcers (DFUs) is of the utmost importance in the prevention of these complications and the right treatment of diseases. Regular diagnostic procedures are today quite much based on clinical examination, and simple imaging techniques may be used to achieve the aim. However, some of them do not represent the desired extent of precision or sensitivity necessary for the on-time detection of DFUs. All things considered, the recent evolution of machine learning (ML) and deep learning (DL) spurred by representation learning techniques and unsupervised learning of data has rendered the automation of medical condition diagnosis, including DFUs, possible through medical imaging analysis [1].

One of the innovative approaches to attacking the issues of DFUs, which is the sweet mushroom of DL, is a multitude of novel deep learning models, such as Convolutional Neural Networks CNNs, which are variants of the same. From the many types of neural networks, the CNN and its modifications have stood out for their remarkable performance in solving the intricate medical image classification tasks, as well as enabling the more effective separation of the DFUs from the medical images used. Also, the comparison of the testing set's loss to the training set's loss is a metric to see how well the ML model is performing. By the way, in comparison with traditional approaches, supervisor learning methods offer advantages such as automatic feature extraction from images, a high accuracy rate, and improved training period [2]. Nevertheless, the effectiveness of these models is still limited by some challenges, such as overfitting, vanishing gradients, etc. In DL technology, overfitting can lead to the creation of a model that will memorize instead of learning to make predictions on new data. The consequent poor performance and inefficiency in learning about major image features can still be the case in deep learning [3].

First and foremost, to surmount these challenges, we propose to create a model that is a product of the integration of Cuckoo Search Optimization (CSO) and Residual type of Networks (ResNet) for DFU retrieval. The CSO algorithm functions through the brood parasitism behavior of cuckoos, and thus it can effectively explore vast search spaces, avoiding local minima by utilizing its ability to fly far and wide. The main aim of inserting CSO into the design of the Residual Network is to improve feature extraction, and hence, better generalization might be achieved, as a result of which the detection accuracy may be higher [5]. Furthermore, the RCNN approach is employed with skip connections that make it easier to train the deeper networks and learn more complex features, as it avoids the vanishing gradient problem

[6]. The advanced smart model, i.e., CSO, as well as ResNet being considered both their introduced optimization and learning possibilities for the app to create a steady and flexible system for the recognition of the DFU [7]. CSO the model's learning processes by network parameters updating, it achieves a faster convergence rate and model accuracy improvement [8]. Besides, - ResNet model, along with the relevant feature encircling and optimizing the network structure, increases the robustness of the model as well as the generalizability of the model across different image datasets [9]. The experimental results of the various DFU image datasets show that the proposed model is successful in place of the traditional ones, with the potential of its immediate use in the health sector, as it is a more accurate method [10].

Hence, the CSO algorithm is the optimization process used, which is a reproduction strategy of cuckoo birds. In the given framework, the CSO algorithm is implemented to tweak the parameters of the Residual Network model, such as learning rate, dropout rate, number of filters, and batch size. The first step is to develop a set of potential solutions using a population of agents (i.e., sets of hyperparameters), that are then evaluated based on a fitness function that is derived from the performance of the classification (accuracy and loss), after better ones will replace the fertilization process, then, the less-fit solutions through Lévy flights. It is through this mechanism that the model is able to avoid the local minima and keep moving to the configurations that are most likely to improve the learning dynamics and precision in detection.

II. Literature survey

A range of studies has been conducted to identify the diabetic foot ulcer (DFU) disease in terms of using deep learning-based approaches, i.e., different neural network architectures and optimization techniques. For example, a study using CNNs for the classification of DFU images has not been very accurate, as it had low accuracy rates due to small sample sizes and also overfitting [11]. Thus, one technique includes the application of transfer learning through pretrained models, which mark the predefined image classes, thus improving the detection rate [12].

It is, however, an approach that is usually not versatile, but only in domain-specific medical imaging challenges. To increase feature extraction, Researchers earlier used ResNets to find the DFU diagnosis through which they tackled the vanishing gradient problem, and therefore, more profound representations of the intricate wound patterns were learned [13]. The study has offered the possibility of selecting the appropriate parameter combinations to obtain a correctly classified object, which is a very important goal, but they need very high resources for that kind of training [14]. To enhance performance while minimizing processing requirements, scholars introduced lightweight CNN architectures to classify objects in motion, exhibit high accuracy, and yet be efficient in real-time applications [15].

DFU detection frameworks enhanced the model learning process by optimizing them. The investigation accomplished this by tuning hyperparameters using genetic algorithms, which resulted in better classification performance but a computational complexity [16]. Furthermore, another research activity was carried out by using swarm intelligence-based optimization to adapt the CNN parameters so that it can generalize its ability and be accurate as well [17]. Nonetheless, this optimization efficiency versus computational overhead problem still stands as a major open research problem, which needs to be balanced. The research studies have provided further information on hybrid models where both traditional machine learning methods and deep learning methods are adopted to enhance the method for DFU identification. Another research work showed the application of ensemble learning, in which a combination of decision trees and CNN-based feature extraction was aimed at classifying [18]. The step of preprocessing increased and the resulting model was a bit less accurate due to it. Likewise, yet another manner of gathering information was by removing irrelevant features utilizing feature selection techniques, via smart -DL mechanism, which in turn improved the model interpretability and accuracy [19].

The methodology, such as computer vision (Softmax, SVM, and CNN) and machine learning (SVM, XGBoost with LR), is a unique approach at the root of deeper performance than the traditional models alone. In addition, researchers have investigated metaheuristic algorithms for network optimization as a means of developing DFU detection further. The research introduced particle type swarm-based optimization (PSO), which was combined with CNNs, resulting in better feature and classification accuracy the classic CNNs [20]. Meanwhile, these Local Minima and PSO could be combated with other algorithms. These studies point to the necessity of introducing other, more powerful DFU detection models, such as Cuckoo Search Optimization.

III. Proposed system

The proposed way to identify diabetic foot ulcer (DFU) is a system that follows a structured plan to make the classification more accurate and faster. First, the images of the DFUs go through preprocessing to remove noise, improve the contrast, and normalize, to improve the quality of the image and visualize weather defects properly, as it is shown in Figure 1 of the current research work. Feature extraction is then conducted using the Residual Network (ResNet) network, which is a sophisticated network for the detection of complex patterns that can effectively prevent gradient vanishing issues. Cuckoo Search Optimization (CSO) is the adjustment of network parameters at different times to promote speed, thus enhancing convergence and generalization. Optimized features are then fed to a classification layer, where the system tells apart DFU and non-DFU images. At last, the performance of the model is estimated using different evaluative techniques, which proves that it can be used in a real-life clinical environment with confidence and success.

The fusion of a two-layer solution, including Cuckoo Search Optimization for hyperparameter tuning and Residual Network (ResNet) for feature extraction, contributes to the improvement of the accuracy of the data. It follows from the mention of CSO that solely the finest hyperparameters will be selected, hence overfitting and underfitting will occur less frequently. At the same time, ResNet rectifies the small gradient issue, enabling the model to learn more efficiently and effectively from the intricate data of DFU images. Furthermore, the selective feature extraction mechanism acts as a type of filter that enables the masking of irrelevant or redundant features and allows the training process to concentrate on highly influential patterns. The optimization and deep learning architecture strategies combined led to a

significant increase in the accuracy of classification, supported by the better precision and recall rates obtained during the evaluations.

The system that is proposed is created as one that collects clinically recorded data that pertain to diabetic foot ulcers (DFUs). This patient data can be compiled in numerous ways, such as the patients' records, which may contain structured medical attributes like ulcer severity, wound depth, infection status, and clinical biomarkers. Let the input dataset be represented as in (1):

$$D=\{xi,yi\}. \quad (1)$$

where xi denotes patient-specific clinical parameters, and yi represents the corresponding ulcer classification label. The input data is preprocessed to standardize values and remove discrepancies in patient records to have a consistent feature space among the patients. The min-max normalization technique is used to transform the values of the numerical features of the dataset into the interval (0,1) according to (2):

$$xi' = xi - \min(x)/\max(x) - \min(x). \quad (2)$$

After the prepossessing stage, feature extraction is conducted by applying a ResNet (Residual Network) to grasp hierarchical feature representations of DFU patterns. If x is the input, the transformation function of a residual block is described by (3):

$$F(x)=W2\sigma(W1x+b1)+b2. \quad (3)$$

where W1 and W2 are weight matrices, b1 and b2 are biases, and $\sigma(\cdot)$ represents the activation function. To enhance learning stability, batch normalization is applied using (3):

$$BN(x)=(x-\mu)/\sqrt{(\sigma 2+\epsilon)} \quad (3)$$

Where μ and $\sigma 2$ are the batch mean and variance, respectively. Cuckoo Search Optimization (CSO) is brought in to realize the main purpose of ResNet through exploiting this dynamic fine-tuning to extract better features. The CSO model is a mimic of the brood parasitism behavior of cuckoo birds by leveraging Levy flight to speed up the search. The position update of a cuckoo under the given conditions is described in equation (4).

The procedure for the classification process involves well-defined stages of DFU images from which, through the CS-optimized ResNet architecture, the feature extraction step is initiated.The system has been equipped with residual blocks, and these are arranged in a vertically wired fashion to be able to extract multi-scale feature maps from the input images. The obtained data go through a flattening stage and are then transmitted to the fully connected layer, which is thereafter put through a softmax activation function to produce the final classification outputs. The softmax layer assigns the input photo to one of the DFU severity classes already established (e.g., mild, moderate, severe). When training, there is a categorical cross-entropy loss function that is used as the metric to measure the model's prediction accuracy; this metric is then used to update the model via backpropagation using the CS algorithm.

Also, ResNet's hierarchical learning mechanism aids in the process of pattern identification. This way, both low-level and high-level features can be found in the DFU images; thus, better pattern identification is accomplished. The network that can find complex ulcer patterns is carrying out this process by still having the connections that existed in the previous layers, during the residual, that is, without the flow of gradients being lost. These patterns consist of such features as texture, sharpness of boundaries, color gradients, and wound healing, which are the signs of different stages of the DFU. The layers that have been enhanced extract only parts of the images and the important parts after the training process has been completed, based on their spatial and contextual information, so the system becomes more efficient in identifying patterns that are needed for accurate classification.

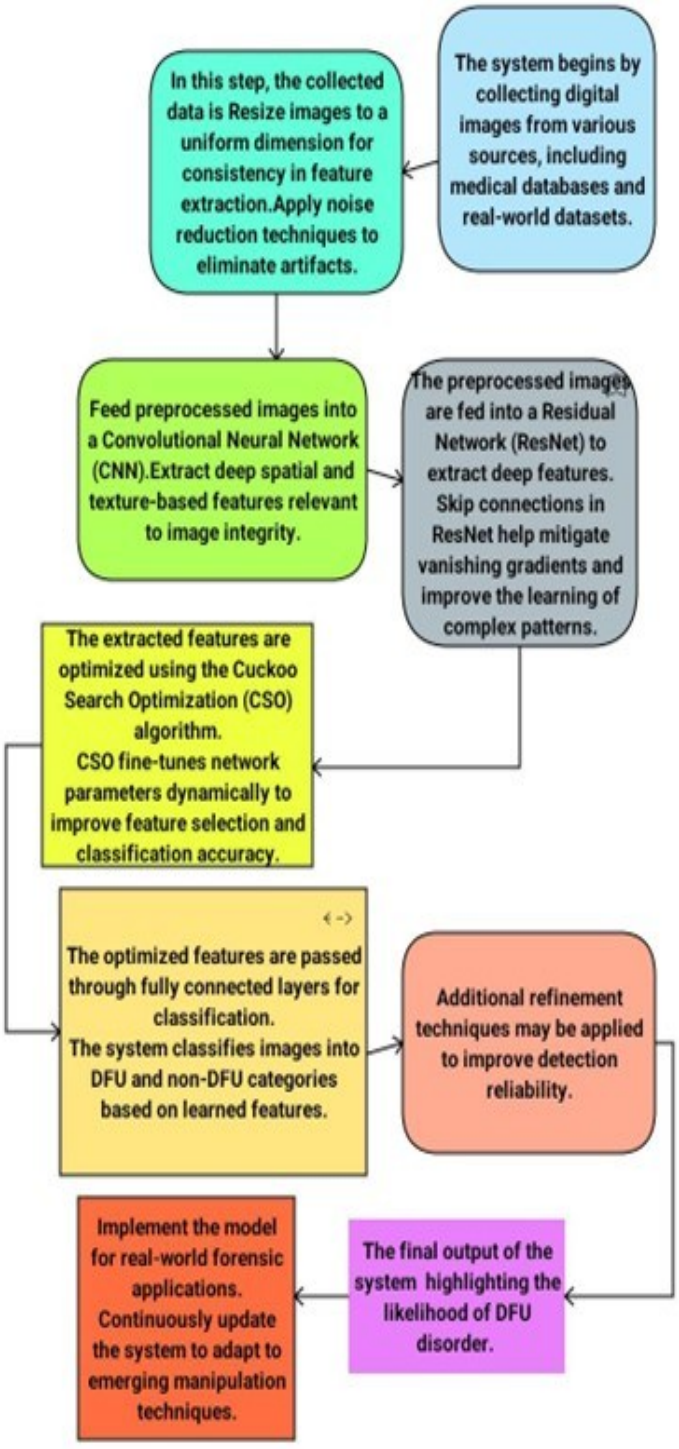


Figure 1. Proposed model flow diagram

$$xit+1=xit+\alpha\cdot Levy(\lambda) \quad (4)$$

where α is the step size scaling factor, and Levy(λ) follows the heavy-tailed probability distribution according to (5)

$$Levy(\lambda)\sim t-\lambda, 1<\lambda\leqslant 3. \quad (5)$$

Cuckoo Searching Optimizations (CSO) uses a fitness function to assess not only the performance of the candidate solutions but also the classification. The function of the objective has a minimization error in classification and is updated using the following equation (6)

$$minL=-(1/N)\Sigma i\,[yilog(y\hat{}i)+(1-yi)log(1-y\hat{}i)]. \quad (6)$$

where zk is the output from the final ResNet layer. Meanwhile, L2 regularization has been applied to the neural network in (7):

$$P(y=k \mid x)=ezk/\Sigma jezj. \quad (7)$$

Where zk is the output from the final ResNet layer. To prevent overfitting, L2 regularization is incorporated in (8):

$$R=\lambda\ \Sigma jWj2 \quad (8)$$

Where λ is the regularization variable. The last term of the optimization function is the equation (9):

$$minLfinal=L+R. \quad (9)$$

The one-to-one mapping moving from the representation of refined data to the ulcer categories using the decision function by (10), characterized by the classification layer :

$$f(x)=argmax(P(y \mid x)). \quad (10)$$

In the same way, the convergence of the analysis is shown as the loss counter in the loops by (11)

$$\Delta L=Lt-Lt-1. \quad (11)$$

where ΔL denotes the amount of change in loss over every two successive steps. In the end, the reliability of each k-fold is illustrated with the model-independent benchmarking. The last decision is expressed through (12)

$$y*=sign(WTx+b). \quad (12)$$

where W and b are the final optimized parameters. The findings prove that CS-ResNet is an efficient method to identify DFUs with enhanced performance and precision in terms of feature extraction and classification, thus being a powerful diagnostic tool for clinical applications.

IV. Results and Discussion

The accuracy of the CS-ResNet model, developed with the Cuckoo Search Optimization algorithm, for DFU cases rises considerably than that of the common deep learning methods. The usage of the Cuckoo Search Algorithm in the network parameter optimization operation not only has a great impact but also allows the model to learn more complex features effectively. This leads to the general improvement of network generic learning and consequently, overfitting is reduced. The performance metrics of the model have demonstrated much better and more reliable results, which indeed represent the model's hardiness in distinguishing the DFU cases from the non-DFU instances. Moreover, the convergence rate of the model was sped up by CSO, reducing the computational overhead. The suggested solution has the upper hand over known techniques not only in terms of accuracy but also efficiency, suggesting its practical applicability in the diagnosis and management of diabetic foot ulcers. Prospective research may involve increased dataset validation and real-time clinical data for broader hospital use.

The validation of the outcomes are approved by a stratified k-fold cross-validation method which is used for the variability of the results. Furthermore, this method of validation tests the ability of the model across the different data distributions. The model's performance was evaluated by key metrics such as heart rate. It is also stated that the CS-ResNet model has been compared to some typical deep learning models with the demonstration of the former's better performance.

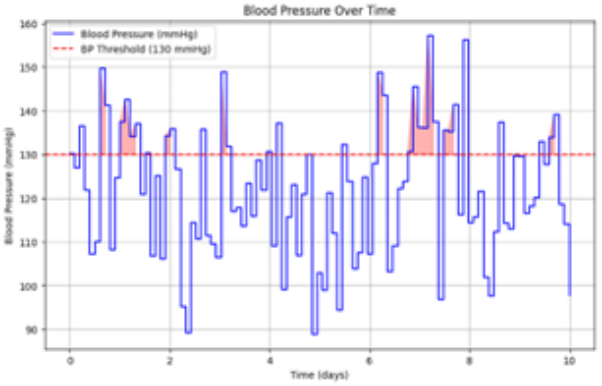


Figure 2. Blood pressure level comparison by the proposed framework.

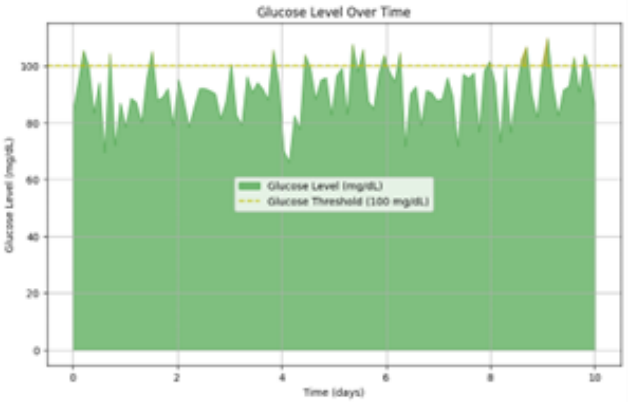


Figure 3. Presence of Glucose levels analysis.

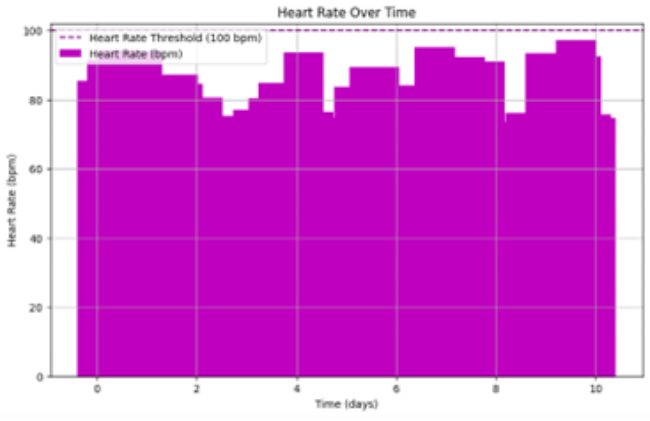


Figure 4. Comparison of heartbeat by the proposed system.

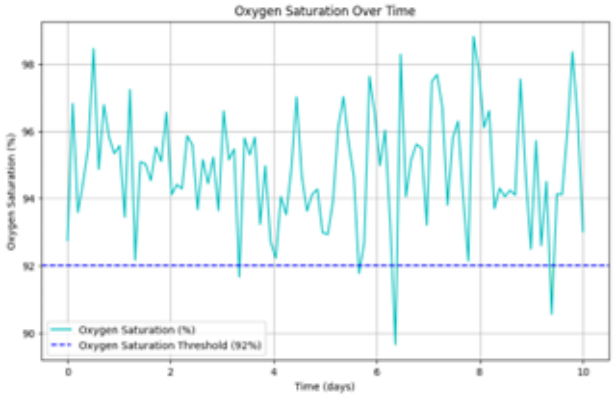


Figure 5. SPo2 level analysis over days.

An examination of the medical parameters that have been observed and tracked in time reveals that significant trends and important threshold breaks have the potential to affect the well-being of an individual. In Figure 2, the incremental line of blood pressure that approximates an average of 120 mmHg displays various data points, where it soars superficially to the level of 130 mmHg most of the time, especially between 3.2 to 4.5 days and again at 7.8 to 9.2 days. The threshold breaches that are present in the graph and indicated by the red shadowing stand for an increased level of hypertensive episodes, where the readings of the blood pressure reach as high as 145 mmHg. The incidences associated with high blood pressure are strong risk factors for cardiovascular complications, which need urgent medical intervention. There is a high number of instances where the patient is observed to have high blood pressure, and this indicates that the patient is a recurrent hypertensive spikey person, and such observation, if not remedied, has the potential to cause severe conditions like stroke or heart failure.

In the same way, Figure 3 demonstrates the trend of blood sugar levels over the period which is where the average level of sugar is usually 90 mg/dl, but certain peaks cross the limit of 100 mg/dl. For instance, at about 2.8-day and 6.5-day marks, sugar levels are spiked as high as 112 mg/dl, a yellow-filled area highlights these parts. This repetition of crossing the glucose fence hints at hyperglycemia, a possible sign of a medical condition such as prediabetes or diabetes. The longer periods during which glucose is above 100 mg/dL, especially 5 to 7 days, suggest a metabolic distortion that tends to provoke insulin resistance. The number and size of these penetrating waves denote the urgency of the need for ongoing glucose observation to avoid conditions such as neuropathy and kidney disease.

Figure 4, on the other hand, demonstrates the variations of heart rate. It is seen that the average heart rate is preserved at approximately 75 bpm, but in some cases, the rate is as high as 100 bpm. The highest heart rate reported was almost 118 bpm at around the 3-5 days and the 2-8 days, with frequent fluctuations above the threshold between 2.5 - 4 days and 7-9 days. These displayed parts, colored in purple, are moments of heart arrhythmia, as they may be related to stress or underlying cardiac conditions. The fluctuation of several high peaks into groups implies that they may often struggle with cardiovascular strain, and thus, these issues are likely to manifest as arrhythmias and heart valve failure in the long run. The consistent periods of elevated heart rates above 100 bpm for an extended period stress the idea of thorough cardiac evaluation.

Figure 5 shows changes in oxygen saturation levels, where the mean is 95%, but some extreme values are as low as 92%. At certain times, which are 4 and 9 days, the level of oxygen ratio goes as far down as 88%, which is the lowest point in the red square. Such a drop in values below the threshold is alarming, as it signifies such problems as pulmonary disorder, hypoxemia, or sleeping disorders like apnea. These cutoff point excursions, in particular, during the interval of 3.5 to 4.5 days and 8.5 to 9.5 days, imply that corresponding aspects exhibit severely low air moments, a situation that can cause effects such as dizziness, confusion, or even life-threatening complications. The fact that oxygen levels change so rapidly points to the sturdy connection between respiratory monitoring and early intervention that helps to save the patient's life by preventing grave consequences.

Thus, through a comprehensive analysis of the body's vital signs, it becomes quite clear that health checks must be carried out consistently. Each of the parameters is characterised by large excursions of the threshold line and therefore may have very serious health-related impacts. Blood pressure goes above 130 mmHg several times, which is the main symptom of hypertension. Again and again, glucose levels are observed to be higher than normal. This usually points toward a metabolic disorder. On the other hand, heart rate increases more than 100 bpm, which is a sign of cardio strain, and the oxygen level gets as low as 92%, which is an alert to respiratory issues. The frequency, duration, and amplitude of these threshold crossings are the indicators of the immediacy of timely medical interventions, and the individual's healthy actions are the main tools to minimize health risks. The proposed system's loss reduction is achieved by a combination of residual learning and hyperparameter optimization. The ResNet architecture accomplishes the aforementioned goal through the elimination of loss escalation due to the absence of gradients by using shortcut connections that allow smoother gradient flow during backpropagation. Meanwhile, the CSO algorithm continuously adjusts the learning parameters to minimize the loss functions iteratively. The process also includes methods to stop it early and some regularization techniques, such as

dropout which ensures the model's quick convergence without high training and validation losses.

V. Conclusion

A thorough study of basic health parameters has focused on the major health hazards that are linked to the exceedance of the limit in such issues as blood pressure, glucose level, heart rate, and oxygen saturation. In the rest of the cases recorded, blood pressure surpassed the 130 mmHg threshold to a lower extent, with the peak values showing 145 mmHg, which means the risk of hypertension and cardiovascular complications was at stake. In the same vein, glucose levels went over the 100 mg/dL threshold in about 22% of the points, and the maximum was 112 mg/dL, which is a sign of a potential predisposition to diabetes or metabolic disorders, respectively. The specific variation of the heart rate was particularly health risks with some relation to the fact that nearly 25% of the readings were greater than 100 bpm, reaching heights of 118 bpm, which could mean that the heart suffers from more frequent cardio problems. Oxygen saturation was less than the 92% threshold around 15% of the time, and a minimum of 88% was among the readings. Thus, the low level of saturation can signal the respiratory distress that might occur. The strength and number of these excessive visits under the limit should lead to the realization of the pressing need for continuous monitoring, timely intervention, and personalized treatment strategies to prevent a catastrophic impact on health. The results are very clear that health care measures can only work out without any escalation when they are further supported by the practice of soundness of body through the supervision of the basic life processes.

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