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Algorithmic Decision Systems: Design, Transparency, And Accountability In AI Models

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Abstract
Algorithmic Decision Systems (ADS) have been widely applied in healthcare diagnostics for facilitating effective decision-making. Nevertheless, insufficient transparency, accountability, and interpretability in Artificial Intelligence (AI) systems still pose considerable challenges, especially in life-critical healthcare applications. To promote accurate and AI-driven decision support for healthcare, this research presents human-centric healthcare diagnostic approach by applying the Intelligent Ant Lion Optimizer-Dense Convolutional Network (IntALO-DenseCNet) model, which enables reliable classification while guaranteeing trustworthy AI-based decision-making. Data utilized in proposed model are in form of structured healthcare datasets, including patients' demographic information, diseases, medications, and diagnostic information. Data processing usingmin-max normalization and standardization to preprocess collected data. Additionally, dimensionality reduction is performed using Linear Discriminant Analysis (LDA). The proposed IntALO-DenseCNet decision system for healthcare diagnostics integrates the optimal solutions generated by IntALO for feature selection and parameter tuning. Finally, this research proves that proposed approach ensures high levels of transparency and accountability through interpretable output, confidence score, and decision trace capabilities. Experiments (Python) conducted in the research indicate that IntALO-DenseCNet is capable of achieving state-of-the-art performance at 97.5% accuracy and 97.96% precision. The proposed IntALO-DenseCNet architecture provides clear, accountable, and very precise health diagnosis systems, showing its efficiency as an effective human-centric AI decision-making system.

Keywords: Decision System, Accountability, Dense Convolutional Network, Healthcare Applications.

1. Introduction

Human-Cantered Artificial Intelligence (HCAI) in healthcare prioritizes individualized and person-cantered models for patients and healthcare professionals. HCAI addresses issues including the alignment of Artificial Intelligence (AI) and medicine, biases in algorithms, and ethical use of AI technology [1]. Precision medicine adoption into healthcare: Precision medicine focuses on individualized treatment based on patients' genetics, and biomarkers. AI helps improve diagnostics and treatment through enhanced healthcare management. Chronic illnesses and the growing aging population have increased the need for effective healthcare provision. Accountability, transparency, and bias remain major challenges in AI-assisted healthcare decision-making [2, 3]. The limited interpretability of AI systems makes clinical decisions difficult to understand. Inaccurate or biased predictions can negatively affect underrepresented patient groups, increase healthcare disparities and raise ethical, legal, and trust-related concerns [4].Pneumonia and Tuberculosis are critical chest diseases with overlapping patterns in chest X-ray images, making accurate diagnosis challenging. Chest X-rays offer a cost-effective and non-invasive diagnostic solution that supports early disease identification, and efficient clinical assessments [5]. Automated systems in healthcare, with the help of AI, can analyze biomedical data effectively and accurately, which helps in making better decisions and efficient healthcare management.AI models contribute to diagnosing diseases using abnormalities detected via Magnetic Resonance Imaging (MRI) and X-rays. Early disease diagnosis, personalized treatment plans, ongoing patient monitoring, and chronic disease management [6].

Research Aim: This research seeks to build an open, responsible healthcare diagnostics system based on the suggested IntelligentAnt Lion Optimizer–Dense Convolutional Network (IntALO-DenseCNet) model. The goal of this research is to increase accuracy in predicting diseases, optimize the feature selection and network settings, decrease biases, and make the process more interpretable and reliable within the model of Human-Centric Algorithmic Decision Systems (ADS).

Research Organization: Section 1 gives an overview of the background of algorithmic decision systems in healthcare, Section 2 provides a literature review on AI-enabled medical diagnoses, Section 3 presents the methodology used, including pre-processing, feature extraction, and the proposed IntALO-DenseCNet model, Section 4 includes result evaluation and performance analysis, and Section 5 shows the conclusion of the research.

2. Related work

Research [7] was conducted to detect and locate any diseases that occur within the chest using the X-ray images. This approach used the Gated Vision Transformers (GViT) technique for classifying the disease, while the Swin Transformer Version 2 was used for locating and segmenting. Accuracy above 0.95 was attained with recall,F1-score, and precision along with 90.98%Intersection over Union (IoU).The proposed approach [8] was to diagnose diseases related to neurology, like brain tumors and Alzheimer's disease, by means of MRI. It used the model, namely Spatial-Temporal Graph Convolutional Network with Vision Transformer (STGCN-ViT), which integrates Vision Transformers (ViT), and Convolutional Neural Networks (CNNs) for extracting spatial and temporal features. It attained accuracy and the precision above 94%; it was computationally intensive. The introduced method was to enhance the discrimination between pulmonary sarcoidosis and lung cancer through chest Computed Tomography (CT) images. Radiology Computed Tomography- Convolutional Neural Network + Vision Transformer (RadCT-CNNViT) [9] incorporated with theradiomics analysis, to extract features and classify lesions. The model demonstrated 93% accuracy and Area Under the Curve (AUC) 0.97%. To enhance classification of cervical cancer by the use of reliable clinical diagnosis with the Densely Connected Convolutional Network with 201 layers (DenseNet201) and InceptionVersion 3 (V3) models [10] integration had been performed based on feature fusion techniques, which provided a highly accurate result with 96.54%. Research [11] involved the use of Swin Transformer along with EfficientNet-B3, Residual Network-50(ResNet-50), stacked classifiers, and Explainable Artificial Intelligence (XAI)to enhance the accurate diagnosis of gastrointestinal diseases using endoscopic images and minimize false negative cases. It managed to attain an accuracy of 93.79%, but the process involved heavy computation costs. The author of [12] designs a robust smart healthcare monitoring system to diagnose diseases accurately. It involves the cloud-based Cellular Internet of Things(C-IoT) architecture, encryption, and an Artificial Neural Network (ANN) algorithm for data processing. The method achieved a diagnostic accuracy of 91%. Research [13] enhanced the generalizability of Machine Learning (ML) models across sites within healthcare for diagnosis purposes. The technique involves utilizing pre-trained models through direct deployment, threshold tuning, and transfer learning approaches and this approach attains a clinical effectiveness with a Net Present Value (NPV) greater than 0.959.The purpose of the research [14] was to enhance the security of smart healthcare systems from malicious attacks. The approach used involves deploying HealthGuard with ANN, Decision Tree (DT), Random Forest (RF), and K-Nearest Neighbors (k-NN) algorithms to identify unusual device behavior. A 91% detection rate and 90% F1-score were obtained. Research [15]was conducted to design a Deep Learning (DL) architecture through transfer learning that can help identify skin diseases quickly and accurately. The VGG16 pretrained model was used to classify chickenpox, measles, monkeypox, and health diseases. The method achieved an accuracy rate of 93.29% in testing, with Layer-wise Relevance Propagation making it more interpretable. Research [16] designs a secure and effective healthcare system based on IoT technology by ML techniques for detecting health status effectively. The approach uses a cloud computing-enabled IoT architecture along with lightweight encryption techniques and ANNs, and achieves 91% accuracy in health diagnosis.

3. Methodology

The healthcare condition diagnosis model, shown in Figure 1, incorporates the Kaggle Healthcare Dataset, which encompasses patient data, such as age, gender, blood group, disease, type of hospitalization, cost of treatment, drug consumption, and lab test data. First, pre-processing techniques are applied to the gathered dataset through normalization and standardization methods. Then, LDA is applied to identify relevant features and conduct dimensionality reduction. IntALO, on the other hand, is used to optimize parameters in the context of feature selection and parameter tuning to maximize the predictive power and performance of the proposed framework. Ultimately, DenseCNet is applied to conduct healthcare condition diagnosis.

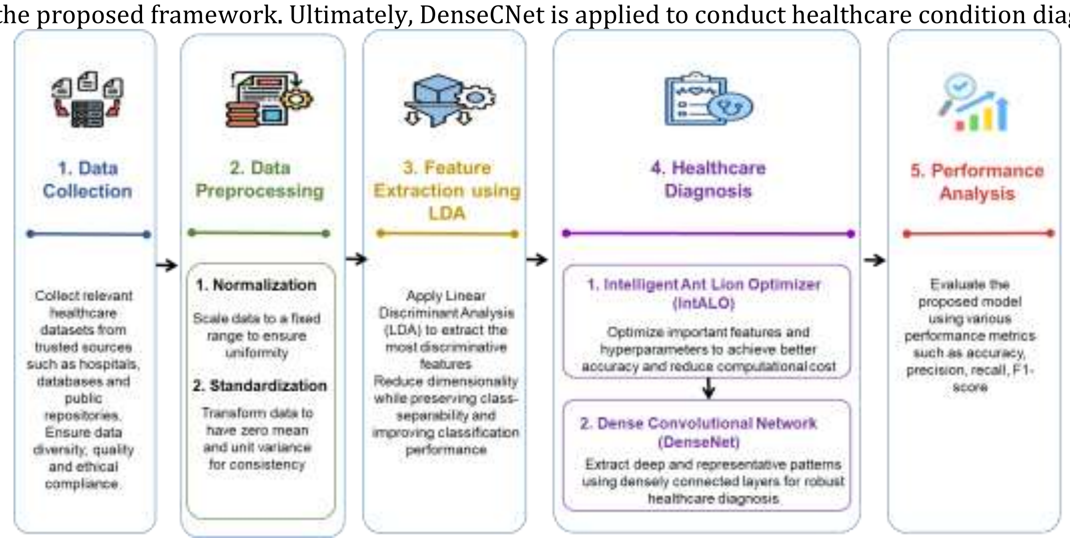

Figure 1: Methodology flow of Proposed Method

3.1 Data Acquisition

Dataset used in this research is derived viaKaggle source (https://www.kaggle.com/datasets/prasad22/healthcare-dataset). Datasetis used for developing and testing the proposed model for healthcare diagnosis prediction. The data set consists of about records 10,000 of patients' healthcare information with various characteristics such as age, gender, blood group, disease state, type of admission, medications, billing charge, and laboratory test data. To test the proposed model, the dataset was partitioned into train set andtestset with a ratio of 80:20.

3.2 Data Pre-processing

Normalization: Normalizing will scale the value of each feature within a range from 0 to 1, thus eliminating any bias due to features with high numerical ranges. Normalization will aid in improving the convergence and stability of the model during training, thus ensuring better health care diagnosis using unbiased features.

$$W_{normalized} = \frac{W_{feature} - W_{min}}{W_{max} - W_{min}} \quad (1)$$

In Equation (1), W denotes thefeature of the weight, $W_{feature}$denotes the health input variables, W_{min} represents the minimum valueof variable in the dataset, W_{max} represents the maximum value of variable in the dataset, and $W_{normalized}$ denotes the value of normalization or transformation of the features for the healthcare dataset.

Standardization: The standardization method is applied to transform the raw data collected from the healthcare domain to an instance where the mean of the data is zero while its standard deviation is one. This approach ensures that patient information such as age, hospital admission details, and medical conditions are presented uniformly. Standardization facilitates stability in the model by reducing bias due to scaling of data attributes.

$$y_{standardization} = \frac{W_{feature} - \mu_W}{\sigma_W} \quad (2)$$

In Equation (2), $y_{standardization}$refers to the value of standardization for the feature of the healthcare dataset, μ_W denotes the mean value of the features over the healthcare dataset, σ_W refers to the standard deviation of the feature over the healthcare dataset, andy denotes value of the standardized feature.

3.3. Feature extraction using Linear Discriminant Analysis (LDA)

LDA is employed for feature extraction to improve classification interpretability in healthcare diagnosis. LDA is a supervised dimensionality reduction technique that aims to maximize class separability by identifying the most discriminative feature representations. This process reduces redundant and irrelevant features while preserving essential class-related information, thereby enhancing the accuracy, efficiency, and overall performance of predictive healthcare models.

$$|K(X)| = \frac{|X^u T_c X|}{|X^u T_X X|} \quad (3)$$

$$T_c X = \lambda T_X X \quad (4)$$

In Equations (3 & 4),K denotes the similarity function of kernel.$T_c$denotes the Class variance matrix, T_X represents the Class-internal scatter matrix, X is the matrix of projection, X^u is the transpose of the matrix X, K(X) denotes the function of the criterion.λ denotes the eigenvalue associated with X.

3.4. Transparent and Accountable Algorithmic Decision Systems for Healthcare Diagnostics using Intelligent Ant Lion Optimizer–Dense Convolutional Network (IntALO-DenseCNet)

The proposed model is designed to integrate the DenseCNet architecture and the IntALO technique for improving healthcare diagnostic accuracy. The use of densely connected convolutional networks by DenseCNet is effective for extracting discriminative features of the medical image in an efficient manner. Through this method, the use of adaptive strategies to explore and exploit features of the medical image makes for improved model performance. The other benefit of this integration method involves the use of the fitness function to test parameter effectiveness.

Dense Convolutional Architecture (DenseCNet): DenseCNet acts as the main DL model for medical diagnoses because it is a model that uses dense connections in its layers, meaning that the features input into the layer at hand come from all previous layers. The dense connections between the layers of a neural network allow for efficient feature reuse and help in learning complex features in the dataset. For medical diagnosis, the DenseCNet model can efficiently learn hierarchical representations of the features and classify the patients' conditions as normal or abnormal.

$$e(q) = \begin{cases} 0, \text{if} q < 0 \\ q, \text{if} q \geq 0 \end{cases} \quad (5)$$

In Equation (5),e(q) is the function for computing the activation output, q is the input value in the activation layer, and the function provides an output of zero to any negative value and positive values, as they are for feature learning in healthcare data.

$$z = KG + a \quad (6)$$

In Equation (6),z is the output feature map, K denotes the weight matrix in the DenseCNet model, G refers to the input feature vector of healthcare data, and a is the bias term.

$$G_2 = \frac{G_1 - E + 2 \times O}{T} + 1 \quad (7)$$

In Equation (7),G_1 denotes the dimension of the input health feature map, and$G_2$is the dimension of the output of health feature map, and E represents the kernel size, O is the padding parameter, and T is the stride.

Intelligent Ant Lion Optimizer (IntALO): The IntALO approach has been applied to ensure accountability and efficiency in the diagnostic procedure of the health care system through parameter optimization. The approach relies on the use of simulation, whereby natural hunting procedures are mimicked to obtain an optimized solution from the search space. In this instance, solutions refer to sets of model parameters that can be used in predicting various medical conditions based on data available from patients. The determination of the optimal solutions can then be done through the fitness function. The IntALO improves upon this approach through the use of adaptive and hybrid methods of optimization.

$$W_j^s = \frac{(W_j^k - b_j) \times (c_j^k - d_j^k)}{(a_j - b_j)} + b_j^k \quad (8)$$

In Equation(8), where W_j^krefers to the value of raw feature j in the iteration k, W_j^s represents the optimal scaled weights of features, which are important after adjusting the value of health feature,a_j and b_j denotes the upper and lower limits of the feature j,$c_j$and d_j are the dynamically optimized search space of the feature$j$,Windicates the ultimate optimized weight for a feature, d indicates the adaptive low search value, c Indicates the adaptive high search value, b indicates the low boundary,a Indicates the high boundary for a medical feature, k denotes the index of the iteration, and$j$ denotes the index of the features.

$$Antlion_i^k = Ant_j^k, u(Ant_j^k) > u(Antlion_i^k) \quad (9)$$

In Equation (9), where Ant_j^kdenotes the candidate solution for the patient problem,$Antlion_i^k$ denotes the elite solution,$u(.)$refers to the function of fitness, Ant refers to the solution for the candidate, and $Antlion$ indicates the best solution.

$$B_{ant\,j}^k = \frac{Q_B^k + Q_F^k}{2} \quad (10)$$

In Equation (10), Q_B^k and Q_F^k are the optimized feature matrices for healthcare features used in adaptive search, $and\ B_{antj}^k$ refers to the optimized healthcare candidate solution in iteration$k$.An upgraded form of ALO to improve its convergence rate is proposed. To achieve this, the process of choosing ants randomly by the antlions is modified in every iteration to help the search move towards the global optima. Mathematically, the above is expressed in Equation (11).

$$B_{temp}^k = \begin{cases} \left(EA\{W_C\} - B_{antj}^k\{W_C\}\right).\times q_1 + B_{antj}^k\{W_C\}, rand > \alpha \\ (ub\{W_C\} - lb\{W_C\}).\times q_1 + lb\{W_C\}, rand \leq \alpha \end{cases} \quad (11)$$

Where,$B_{temp}^k$is the temporary optimized healthcare solution at iteration k, EA is the elite healthcare archive, W_C are the selected healthcare features, $q_1$is the adaptive search coefficient, $rand$ is a stochastic number, α is the threshold parameter for balancing the exploration-exploitation trade-off, lb and ub are the lower and upper healthcare search limits respectively.

$$B_{antj}^k \begin{cases} B_{temp}^k, u(B_{antj}^k) < u(B_{temp}^k) \\ B_{tantj}^k, u(B_{antj}^k) \geq u(B_{temp}^k) \end{cases} \quad (12)$$

In Equation (12), $B_{tantj}^k$is the solution of the healthcare problem that was kept from the previous iteration,$u\left(B_{antj}^k\right)$represents evaluation value of solution, $u(B_{temp}^k)$denotes evaluation value of temporary optimized solution, j is the index for the healthcare characteristics, k is the index for the iteration, and u denotes the function of fitness.The IntALO-DenseCNet model: Transparent & Accountable Healthcare Diagnostics and Decision-Making Algorithm 1 illustrates the process of the transparent and accountable IntALO-DenseCNet model for accurate healthcare diagnostics and decision-making.

Algorithm 1: Transparent and Accountable IntALO–DenseCNet for Healthcare Diagnostics

Input:
Healthcare dataset D
Population size N
Maximum iterations K
Learning parameters of DenseCNet
Output:
Optimized diagnostic prediction model
Begin
Load healthcare dataset D
Preprocess medical images and normalize features
Split dataset into training and testing sets
Initialize DenseCNet architecture
Define convolution, activation, and dense connection layers
Apply activation function using Equation (5)
Compute feature maps using Equation (6)
Update output dimensions using Equation (7)
Extract hierarchical healthcare features from DenseCNet
Initialize IntALO population with N candidate solutions
Set lower and upper search boundaries
Initialize elite antlion solution EA
Set iteration counter k = 1
while (k ≤ K) do
for each ant candidate Bjk do
Scale feature weights using Equation (8)
Evaluate fitness e(Bjk) using diagnostic accuracy
Select elite antlion using Equation (9)
Generate adaptive candidate solution using Equation (10)
Update temporary solution using Equation (11)
Compare current and temporary fitness values
Update optimized solution using Equation (12)
Store best healthcare feature weights
end for
Update global elite archive EA
Adjust adaptive exploration–exploitation parameters
Increment iteration counter k = k + 1
end while

Return optimized IntALO–DenseCNet diagnostic model
End

Hyperparameter of the proposed model: Input images are of the dimension 224×224×3, and the batch size is 32, with 100 epochs of training. Adam optimizer is used with learning rate(0.001)by categorical cross-entropy loss function. The ReLU activation and Softmax output functions have 4 dense blocks with a growth rate of 32.

4. Result

The hardware consists of an AMD Ryzen 9 or Intel i9 13th Gen processor,a 24 GB NVIDIA RTX 4090 GPU, 64GB DDR5 RAM, and a 2TB NVMe SSD make up the hardware. The operating system used is Windows 11 Pro. The hardware has support for CUDA 12.x and cuDNN 8.x. Some of the software tools used include Python 3.11, TensorFlow 2.16/Keras 3, Numpy, SciPy,and Scikit-learn.

Explorative Data Analysis: Figure 2(a) shows the correlation between the age of the patients and the billing amount, where the colored gradient represents the severity level of the medical condition, making it possible to detect the pattern and changes in terms of healthcare cost with respect to different age categories. Figure 2(b) shows the normal and abnormal patterns obtained through learning the healthcare dataset using the DenseCNet model, demonstrating the model's ability to extract feature representations for accurate diagnose of healthcare issues. Figure 2(c) shows the temporal change in healthcare billing cost. This figure helps in detecting variations and fluctuations within the dataset. Figure 2(d) shows the healthcare database based on the age and billing amount of patients.

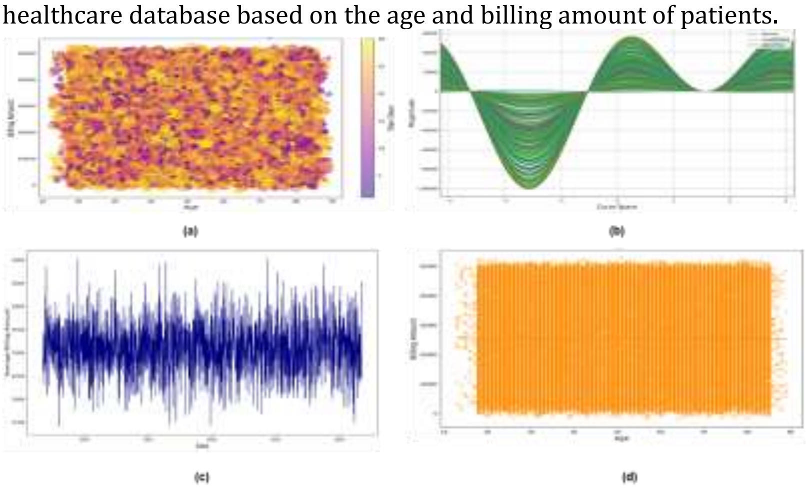

Figure 2: Visualization of Time Trends and Pattern Classification (a) Age and billing amount distribution, (b) Normal and abnormal healthcare pattern analysis, (c) Temporal billing trend analysis, and (d) Healthcare data distribution scatter plot.

Evaluation metrics: The suggested model has been tested on the basis of metrics such as precision,F1 score, accuracy, and recall. While the accuracy denotes the degree of correct predictions, the measures of precision and recall represent the False Positives (FP)and False Negatives (FN), respectively. F1 score is the harmonic mean between recall and precision, giving equal importance to both measures and allowing for determining the accuracy of the model in terms of its FP and FN.

Performance analysis: Experimental outcomes illustrate a marked enhancement in the efficiency of the proposed IntALO-DenseCNet algorithm over conventional ML and DL algorithms. While the F1 scores for the Random Forest, SVM, CNN, and ANN models have improved, their values are between 86.8% and 91.5%. On the other hand, the IntALO-DenseCNet model shows a marked improvement with an F1 score of 97.46%, precision of 97.96%, accuracy of 97.5%, and recall of 96.97%, as shown in Table 1 and Figure 3 below.

Table 1: Comparison of Model Performance

Method	F1-Score (%)	Accuracy (%)	Recall (%)	Precision (%)
RF [16]	86.8	88.4	86.5	87.2

SVM [16]	88.0	89.1	87.8	88.3
CNN [16]	89.2	90.2	88.9	89.5
ANN [16]	91.5	92.5	91.2	91.8
IntALO-DenseCNet [Proposed]	97.46	97.5	96.97	97.96

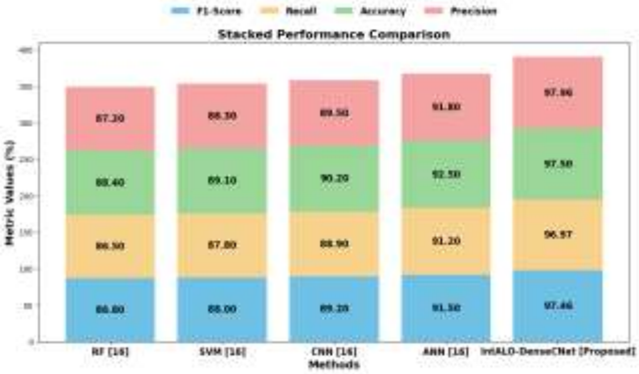

Figure 3:Evaluation of metrics in existing models with the proposed model

Table 2 compares the conventional approaches of ML and DL, which were retrained using the dataset collected from the healthcare sector. Traditional algorithms including RF, SVM, CNN, and ANN [16] performed reasonably well, while the proposed algorithm, known as IntALO-DenseCNet, exhibited excellent performance with precision rate of 97.96% and accuracy of 97.5%.

Table 2:Comparative analysis of Healthcare Diagnostic AI Methods

Method	F1-Score	Accuracy	Recall	Precision
RF	87.8	89.4	88.5	86.2
SVM	85.0	91.1	89.8	89.3
CNN	87.2	89.2	85.9	89.5
ANN	90.5	91.5	90.2	92.8
IntALO-DenseCNet [Proposed]	97.46	97.5	96.97	97.96

Discussion: The proposed IntALO-DenseCNet overcomes the drawbacks of RF, SVM, CNN, and ANN through better feature representation and robustness. The RF [16] algorithm cannot effectively model complex nonlinear mappings and can be easily biased to predominant attributes in high-dimensional space, thus lowering its generalization capacity. SVM [16] suffers from excessive computation time in handling large data sets and high sensitivity to the choice of kernels and hyperparameters, making it unreliable for noisy and overlapped categories. CNN [16] needs considerable amounts of data and time for training and tends to suffer from over-fitting when insufficient data is provided, and the performance depends on appropriate feature design. ANN [16] is frequently confronted with problems such as converging to local optima, high computational complexity, and sensitivity to noisy input data, which limit its robustness and consistency. Unlike those methods mentioned above, the proposed IntALO-DenseCNet can avoid all those shortcomings, with improved deep feature representation, enhanced generalization ability, reduced sensitivity to noise, and balanced precision and recall rates to achieve outstanding classification accuracy and robustness.

5. Conclusion

The above research has demonstrated the development of a transparent and accountable diagnosis model in healthcare with the use of the suggested IntALO-DenseCNet algorithm. Combining the methods such as linear discriminant analysis, DenseNet structure, and IntALO significantly boosted the effectiveness of feature selection, parameter tuning, and the disease classification process. It has been established that the proposed IntALO-DenseCNet model outperforms the other algorithms by demonstrating higher accuracy (97.5%), precision (97.96%), recall (96.97%), and F1 score (97.46%). Moreover, the introduced model increased the level of transparency by providing comprehensible output and promoted accountability by introducing monitoring mechanisms. Thus, the proposed model successfully minimizes the possibility of biases in AI-based healthcare applications. Hence, the suggested algorithm can become an effective ADS for humans in healthcare. The suggested IntALO-DenseCNet algorithm demands substantial computational resources and takes considerable time to train on healthcare datasets of significant size. Further research can be done to incorporate XAI, which helps in making the models more transparent, along with using Federated Learning, ensuring privacy during training.

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