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ENHANCING PNEUMONIA DIAGNOSIS: DEEP LEARNING APPROACHES WITH CHEST X-RAY IMAGES

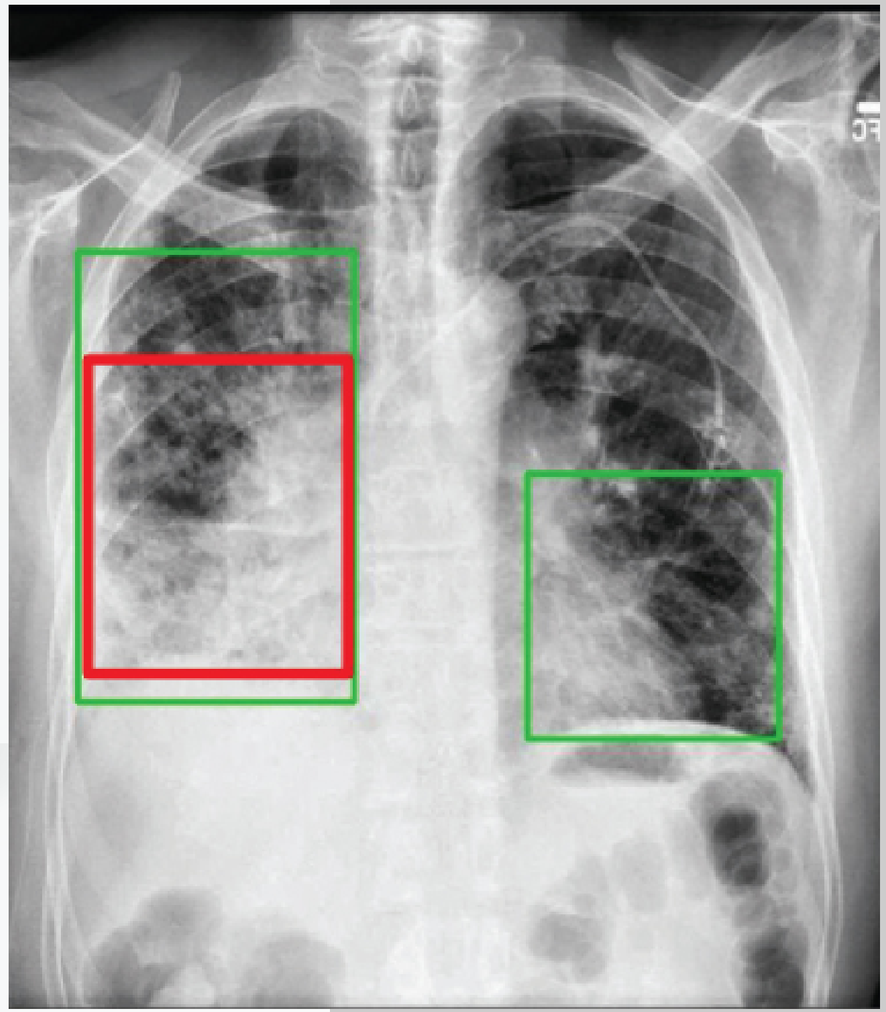
CONTENT

PNEUMONIA

Pneumonia's Ongoing Threat: Pneumonia remains a critical global health concern due to its potential life-threatening nature, emphasizing the urgent need for effective diagnosis and treatment strategies.

Deep Learning Advancements: We Explores the integration of state-of-the-art deep learning models—CNN, ResNet, VGG, and LeNet5—to elevate the accuracy of pneumonia diagnosis from chest X-ray images, potentially revolutionizing the field of medical imaging.

Performance Evaluation and Comparison: Evaluation and comparative analysis of these models will highlight their performance, strengths, and limitations specifically in the context of pneumonia detection, providing valuable insights.



RELATED WORK

2023

D. VARSHNI, K. THAKRAL, L. AGARWAL, R. NIJHAWAN AND A. MITTA

Used Neural Network (NN) with VGG16 on the pneumonia and make classification on it. Obtained accuracy of 92.15%, F1-score of 0.9370, and Area Under Curve (AUC) of 0.9880.

2022

PATRIK SZEPESI AND LÁSZLÓ SZILÁGYI

CNN models to classify the chest X-rays image taken from Guangzhou Women and Children's Medical Center. accuracy of 95.67% which tested with CNN model with no dropout. It also returns precision of 0.9550, 0.9554 recall, 0.9552 F1-score, and 0.9700 AUC

2020

RAHIMZADEH M, ATTAR A

ResNet50 made in propagation formation of the connections between blocks to get better results. With covid chestxray dataset, taken from GitHub repository, the model gets a result of 90.07% accuracy

2019

C.J. SAUL, D.Y. UREY AND C.D. TAKTAKOGLU

CNN with lightened image on increased contrast with ResNet to train the model with dataset about pneumonia and gets an accuracy of 78.73%.

RELATED WORK

2021

B. ALMASLUKH

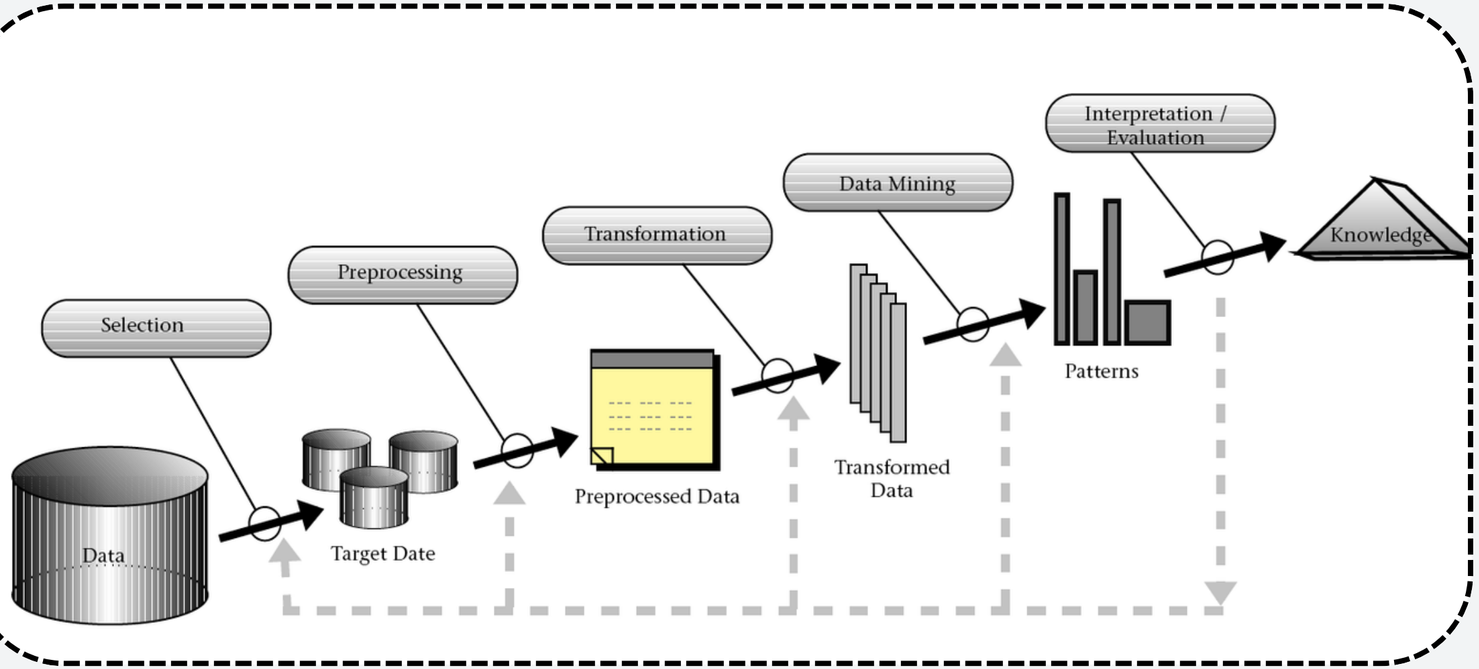
fine-tuned DNN-based feature classification method to process chest X-ray (CXR) dataset. The dataset was split into 3 and used to proceed with 3 experiments. The accuracy for all 3 experiments is 94.4%, 98.9%, and 96.3%

2020

J. E. LUJÁN-GARCÍA ET AL

5232 chest x-ray images of children from one to five years old. When applying the dataset with Xception model, he gets a validation loss of 0.0453 with F1-score of 0.96, which is the best among VGG16 model, ResNet50V2 model, DenseNet121 model, and Xception model.

METHODOLOGY



- Data Preparation: Curated diverse chest X-ray images from Kaggle's pneumonia dataset, preprocessed via batch conversion for streamlined processing

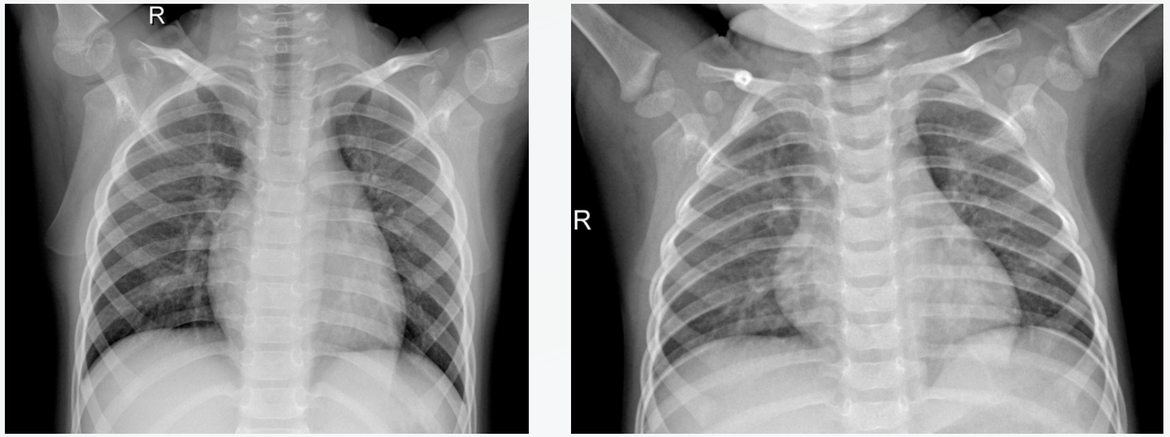
- Model Selection & Optimization: Employed CNN, ResNet, VGG, and LeNet-5 architectures, fine-tuning each for feature extraction from X-ray images, optimizing parameters, and training for enhanced performance.

- Performance Evaluation: Rigorously assessed models using accuracy, precision, recall, and ROC-AUC metrics, gaining insights into their diagnostic capabilities and limitations.

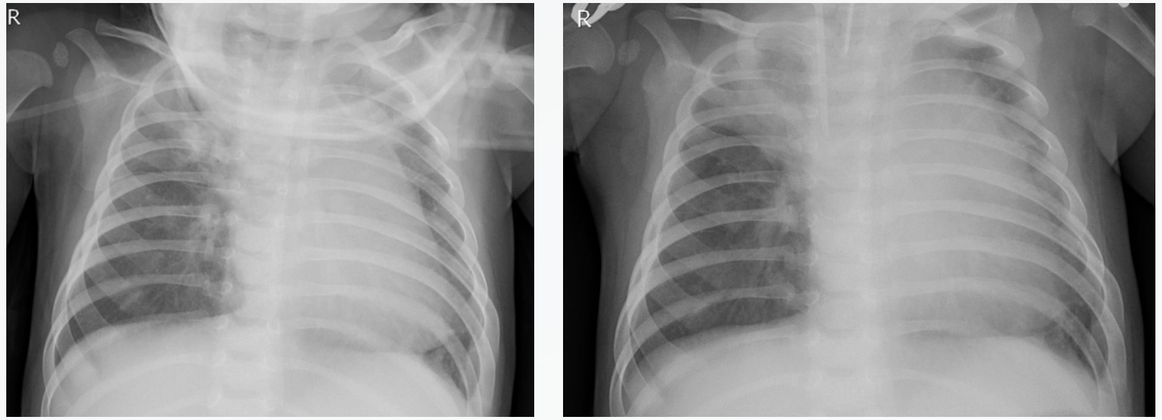
- Visualization and Interpretation: Utilized AUC curves to visualize overall model performance across thresholds, and analyzed training epochs for convergence and stability, providing key insights into model behavior and optimal diagnostic performance.

DATASETS

Publishing Year	2018
Owner	PAUL MOONEY (www.kaggle.com/datasets/paultimothymooney/chest-xray-pneumonia)
Image category	Normal | Pneumonia
Number of Images	[5,842] chest X-ray images, including both normal and pneumonia

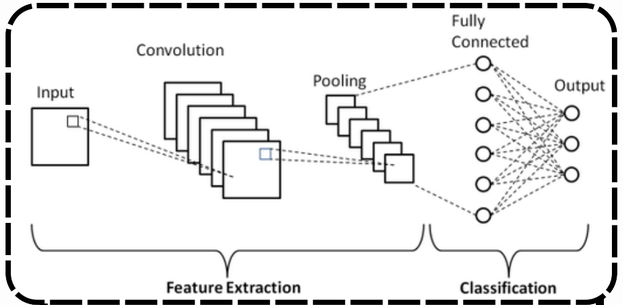


NORMAL



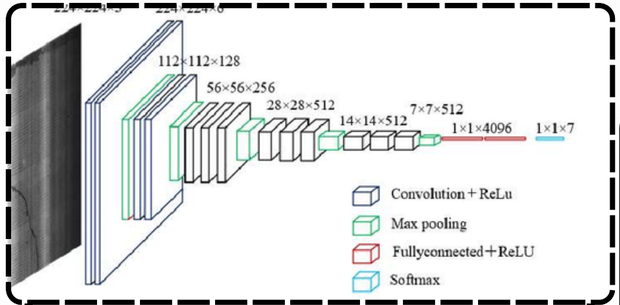
PNEUMONIA

ALGORITHM



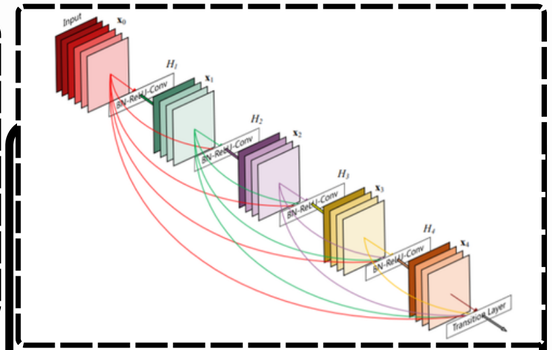
Convolutional Neural Network

Designed to process data with a grid-like topology, convolutional layers, pooling layers, and fully connected layers, image recognition tasks ability to automatically learn features from raw pixel data



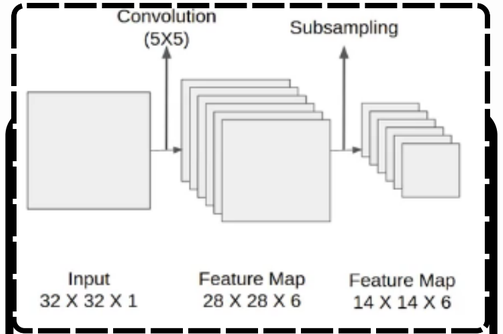
Visual Geometry Group

CNN architecture, key characteristic is the use of very small (3x3) convolutional stacked on top of each other in increasing depth. deeper compared to its predecessors



Residual Networks

neural networks get deeper,skip connections or shortcuts to jump over some layers, enabling the network to learn residual functions. Mitigating the vanishing gradient problem



LeNet-5

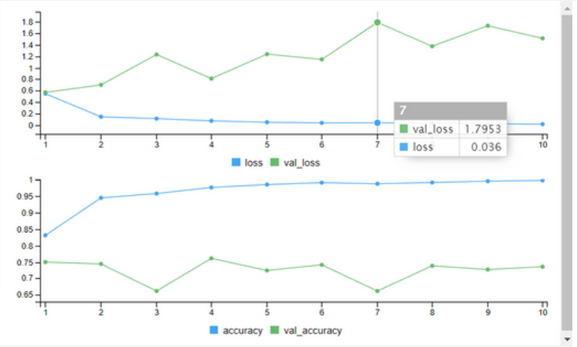
earliest cnn architectures, consist several layer, convolutional layers with learnable kernels and pooling layers

SAMPLE RESULT 40 TRAIN /60 TEST

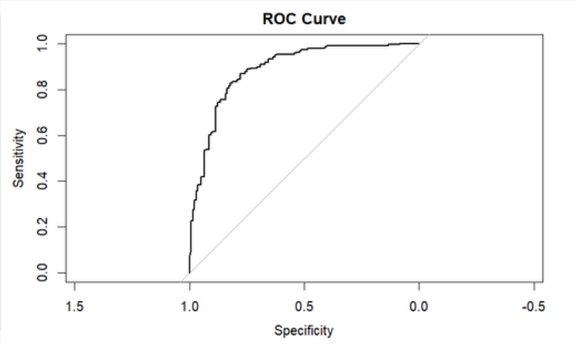
Epoch - one complete pass of adjustments to its weights and biases to improve its predictive ability or minimize the loss function

ROC - (Receiver Operating Characteristic) plot performance of a binary classification true/false correctly/incorrectly identified by model

CONVOLUTIONAL NEURAL NETWORK

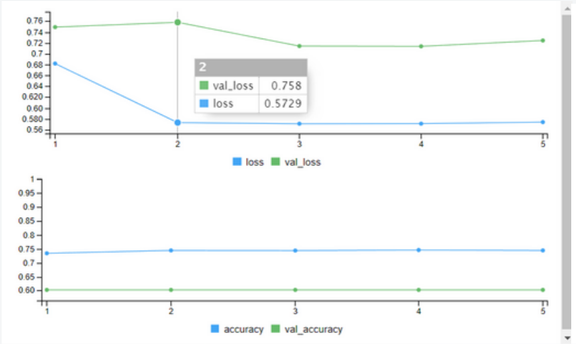


EPOCH



ROC CURVE

VGG (VISUAL GEOMETRY GROUP)



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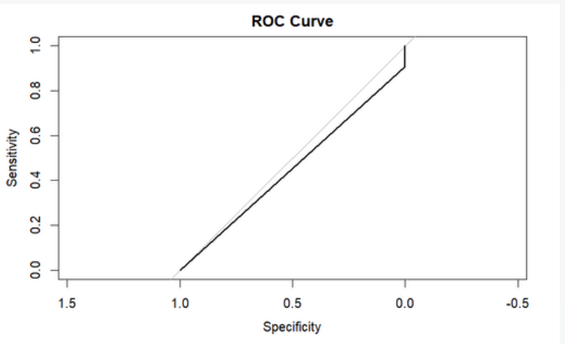
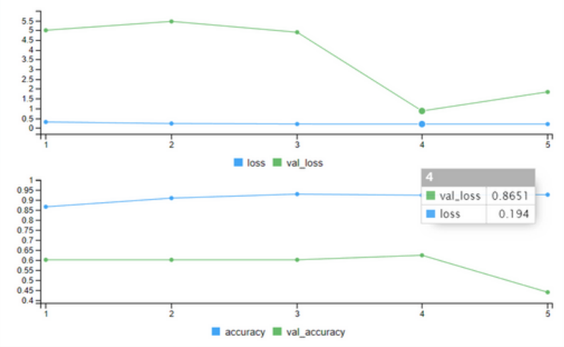


ROC CURVE

RESIDUAL NETWORK (RESNET)



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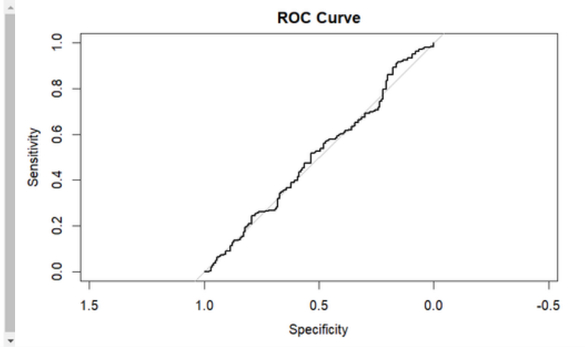
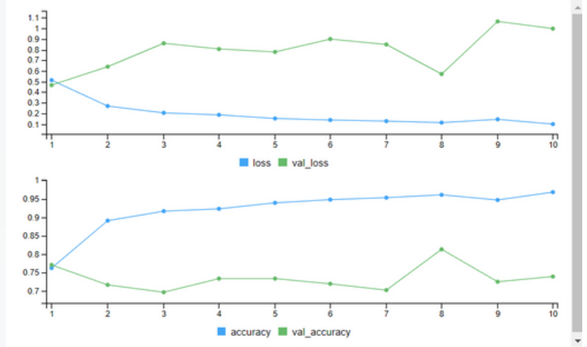


ROC CURVE

LENET-5



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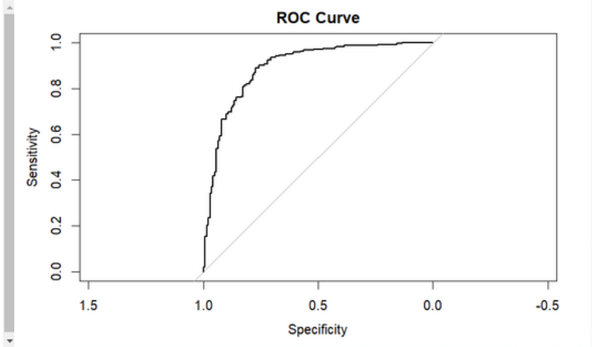


ROC CURVE

ALL THE RESULT

Data split (%)	Algorithm	Error Rate	Accuracy	Precision	Recall	F1-score	AUC
30-70	CNN	0.2476	0.7524	0.7335	0.9780	0.8383	0.9198
	RN	0.3918	0.6082	0.6261	1.0000	0.7701	0.5855
	VGG	0.3918	0.6082	0.6261	1.0000	0.7701	0.5000
	LN-5	0.1635	0.8365	0.8254	0.9524	0.8844	0.9215
40-60	CNN	0.2642	0.7358	0.7183	0.9915	0.8330	0.8882
	RN	0.5597	0.4403	0.6395	0.2350	0.3438	0.5075
	VGG	0.3977	0.6023	0.6257	1.0000	0.7697	0.4530
	LN-5	0.2614	0.7386	0.7219	0.9872	0.8339	0.8923
50-50	CNN	0.3125	0.6875	0.6895	0.9808	0.8476	0.9537
	RN	0.4063	0.5938	0.6250	1.0000	0.7692	0.6475
	VGG	0.4063	0.5938	0.6250	1.0000	0.7692	0.4385
	LN-5	0.2847	0.7153	0.7132	0.9692	0.8217	0.8715
60-40	CNN	0.2455	0.7545	0.7463	0.9808	0.8476	0.9537
	RN	0.4152	0.5848	0.6265	1.0000	0.7704	0.9062
	VGG	0.4152	0.5848	0.6265	1.0000	0.7704	0.5032
	LN-5	0.2500	0.7500	0.7358	1.0000	0.8478	0.9187
70-30	CNN	0.3438	0.6563	0.6824	0.9915	0.8084	0.8971
	RN	0.4938	0.5063	0.6735	0.2821	0.3976	0.5582
	VGG	0.2188	0.7813	0.7832	0.9573	0.8615	0.9099
	LN-5	0.4375	0.5625	0.6257	1.0000	0.7697	0.5000

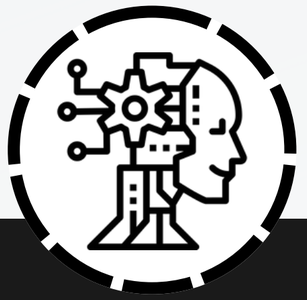
DISCUSSION AND FUTURE WORK

The analysis evaluates CNN, RN, VGG, and LN-5 across diverse data splits, revealing their strengths and weaknesses in error rates, precision-recall, and discriminative abilities. LN-5 as the most proficient algorithm, low error rates (0.1635), precision (0.8365), recall (0.94598), F1 score (0.96531)and AUC 0.9215.

ALGORITHM PERFORMANCE COMPARISON

The CNN model stands out for pneumonia diagnosis with its balanced precision and recall, crucial for accurately distinguishing between normal and afflicted lungs. Its strong discriminative power, reflected in the AUC value, aligns perfectly with the accuracy, precision, and recall needs in medical contexts, ensuring dependable lung condition classification

RELEVANCE TO PNEUMONIA DIAGNOSIS



The analysis proposes advancing AI models in medical diagnostics through refining existing algorithms, exploring novel methods, optimizing parameters, incorporating diverse datasets, enhancing interpretability, and fostering collaborations with medical professionals to ensure effective and reliable diagnostics.

FUTURE RESEARCH FOCUS