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BLOOD TEST AND SCANNING REPORT ANALYSIS USING AI

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Abstract: This project integrates cutting-edge computer vision techniques used to enhance the medical diagnostics by simultaneously addressing two critical aspects of healthcare—blood sample analysis for leukemia and brain hemorrhage classification in MRI images. Leveraging the YOLO (You Only Look Once) algorithm, our system employs deep learning to efficiently detect and classify various stages of leukemia in blood samples. YOLO's real- time object detection capabilities enable swift identification of abnormal cells, facilitating early diagnosis and intervention. The model is trained on a comprehensive dataset, ensuring robust performance across diverse cases. In parallel, Convolutional Neural Networks (CNNs) are employed for the intricate task of brain hemorrhage classification in MRI scans. The CNN model learns complex hierarchical features from brain images, enabling it to accurately differentiate between different types and stages of hemorrhages. This dual-faceted approach aims to provide a comprehensive diagnostic tool, facilitating healthcare professionals in timely and accurate decision-making.

I. INTRODUCTION

In the realm of medical diagnostics, the fusion of artificial intelligence (AI) and healthcare has emerged as a transformative force, revolutionizing the way diseases are identified and treated [1]. This project represents a concerted effort to harness the potential of advanced computer vision technologies in addressing two critical medical challenges: the detection of different stages of leukemia in blood samples and the classification of brain hemorrhages in magnetic resonance imaging (MRI) scans [2]. The first facet of this project delves into blood sample analysis, leveraging the YOLO (You Only Look Once) algorithm, a state-of-the-art real-time object detection system [3]. By employing YOLO, we aim to develop a robust and efficient model for identifying various stages of leukemia in blood samples, enabling early detection and intervention. Simultaneously, the project delves into the realm of neurological diagnostics, employing Convolutional Neural Networks (CNNs) to accurately classify different types of brain hemorrhages in MRI images [4]. The integration of these two distinct yet interrelated tasks aim to provide a holistic diagnostic tool, empowering healthcare professionals with timely and precise information for improved patient care [5]. As we navigate the intersection of AI and medical science, this project strives to contribute to the evolving landscape of healthcare, ushering in a new era of enhanced diagnostic capabilities and, consequently, improved patient outcomes [6]..

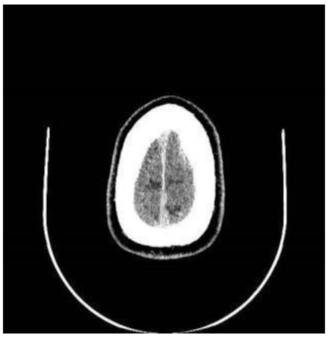

Figure 1. Brain Hemorrhage

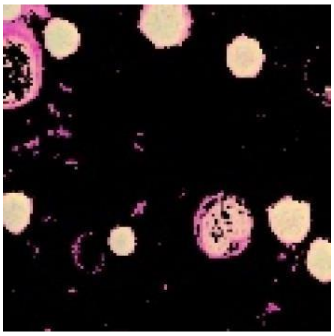

Figure 2. Blood Cells

As per the World Health Organization (WHO), morphological examination and other examinations such as immunophenotype, cytogenetics, and molecular biology, is required in the detection and diagnosis of Acute Lymphoblastic Leukemia(ALL) [7].The Morphological examination is employed to detect leukemia from normal cells, primarily from all types of ALL.

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Differences in the infected cell characteristics from morphological study can serve as a guide for diagnosis and classification of the type of leukemia. Various characteristics in the blood image become hindrances while carrying out morphological study, i.e., blur, noise alteration in staining of the blood smear, overlap of cells, blocking of cells, and cell size and variability [8].

II. LITERARY SURVEY

Hemorrhagic stroke is extremely dangerous to human health. The Rapid development of the system microwave-induced thermoacoustic tomography (MITAT) method has a promising potential to perform brain imaging. Transcranial brain imaging using MITAT remains challenging owing to involved vast heterogeneity in speed of sound and acoustic attenuation of human skull by Chenzhe Li et al [9]. This study proposes to counteract the detrimental effect of acoustic heterogeneity with a deep learning-based MITAT (DL- MITAT) method for transcranial brain hemorrhage imaging. Methods: They designed a new network architecture, a residual attention U-Net (ResAttU-Net), for the proposed DL-MITAT method, which performs better than the combination of traditionally employed networks. They employ simulation technique to construct training sets and accept images obtained by conventional imaging algorithms as the network input. Results: they show ex-vivo transcranial brain hemorrhage detection as proof-of-concept validation. Utilizing an 8.1-mm thick bovine skull and porcine brain tissues utilized to carry out ex-vivo experiments, they illustrate that the trained ResAttU-Net is able to effectively remove image artifacts and precisely restore the hemorrhage spot [10].

Brain Hemorrhage is the bursting of brain arteries due to high blood pressure or blood clotting which can act as a reason for traumatic injury or death. It is the medical emergency where the physician also requires years of experience in order to locate the area of the internal to bleeding before he can perform the treatment. Convolutional Neural Network (CNN), CNN + LSTM, and CNN + GRU deep learning architectures are suggested in this work for Brain Hemorrhage classification. 200 dataset of head CT scan images is used to enhance the accuracy rate and computing capability of the proposed deep learning models. The key focus of this research is to avail the capacity for abstraction by deep learning on a collection of less images as in most critical cases large collections do not remain accessible at hand by Muhammad Faheem Mushtaq and Habib Shah et al [11].

As one of the most frequent secondary complications following traumatic brain injury (TBI), brain edema can cause elevation of intracranial segment water content and increased intracranial pressure (ICP), where the patient will suffer from poor prognosis may result in hemiplegia, aphasia, diagnosis, or even death. Real-time monitoring is very beneficial to promote TBI therapeutic condition and lower mortality and disability rate. Magnetic induction phase shift (MIPS) possesses advantages of non-contacting, good penetration, and real-time bedside monitoring without being invasive. For the present study, 34 rabbits were randomized into the control group (n = 8) and the experimental group (n= 26) for monitoring brain edema by MIPS in 24-h. As controls, simultaneously ICP and BWC were taken as standards. MIPS of rabbits in the model group reduced progressively within 24 h, and ICP and BWC rose by Shuanglin Zhao et al [12]. In addition, sensitivity of MIPS detection became increasingly lower during brain edema evolution. The weights of BWC and ICP calculated by MIPS in three steps were calculated to obtain the index of brain edema severity (BESI), which can quantify the severity of brain edema. The BESI of rabbits in the experimental group grew with time, from 0 to 1. The 0 is normal, and the 1 is severe brain edema. The initial phase of BESI decreased from 0 to 0.43, the second phase from 0.43 to0.917, and the third phase from 0.917 to 1. The BESI of control group rabbits was not increased significantly with time. They were significantly different from each other [13].

Intracranial hemorrhage (ICH) has become a critical healthcare emergency that needs accurateassessment and earlier diagnosis. Due to the high rates of mortality (about 40%), the early classification and detection of diseases through computed tomography (CT) images were needed toguarantee a better prognosis and control the occurrence of neurologic deficiencies. Generally, in the earlier diagnoses test for severe ICH, CT imaging of the brain was implemented in the emergency department. Meanwhile, manualdiagnoses are labour intensive, and automatic ICH recognition and classification techniques utilizing artificial intelligence (AI) models are needed by Noha Negm et al [14]. Therefore, the study presentsan Intracranial Hemorrhage Diagnosis using WillowCatkin Optimization with Voting Ensemble (ICHD-WCOVE) Model on CT images. The presented ICHD-WCOVE technique exploits compute vision and ensemble learning techniques for automated ICH classification. The experimental analysis of the ICHD-WCOVE approach can be tested by a medical dataset and the outcomes signified the betterment ofthe ICHD-WCOVE [15].

Computer vision research into detection and classification of the subtype Acute Lymphoblastic. Leukemia (ALL) has made computer-aided diagnosis more accurate. Another is to act as a second opinion and aide to physicians and hematologists in diagnosing the ALL subtype. Early detection also depends on computer-aided diagnosis in identifying the first line of treatment.

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The purpose of this research is to discuss the evolution of research in ALL subtype detection and classification. The discussion under method involves applying deep learning to object detection and classification. Motivations, challenges, future research directions and recommendations are discussed in detail to acquire and enhance understanding and development in this research field. The research was conducted in a systematic manner by reading a sequence of articles on the detection and classification of ALL subtypes in science direct, IEEE, and PubMed from 2018 to 2022 by Tanzilal Mustaqim et al [16].

Leukemia is not only death-promoting in nature; it is very costly as well to treat. Yet the early detection of leukemia can save patients' lives and money, particularly among children amongst whom leukemia as a form of cancer is very prevalent. What we discuss here in this paper is an explainable supervised machine learning model that precisely predicts the probability of early-stage leukemia based on symptoms alone. The model is constructed on the basis of primary data that are gathered from two of the most prominent hospitals in Bangladesh.

Sixteen characteristics of the datasets are gathered by a survey among leukemia and non-leukemia patients visiting a specialist doctor. Our supervised explainable model is constructed with a decision tree classifier that produces much better results than other algorithms and delivers explainable rules ready to deploy. We have successfully used Apriori algorithm to generate understandable rules for the prediction of leukemia by Mohammad Akter Hossain et al [17]. Moreover, feature analysis and feature selection are done on the dataset to demonstrate the strength of each feature and to increase the accuracy of the classification models.

Different classifiers are tried out on the dataset to show how the simple yet interpretable model that we have proposed performs much better than most other models which we have used. Our proposed decision tree model has yielded 97.45% accuracy, MCC of 0.63 and area under Receiver Operating Characteristic (ROC) curve of 0.783 on test set. We also published dataset and source code of the methods used in this paper [18].

III. METHODOLOGY

A. OVERVIEW : The Detection techniques are pivotal for identifying brain hemorrhage and leukemia blood cells. In the case of brain hemorrhage, algorithms are trained on medical imaging data, such as MRI or CT scans, to discern patterns indicative of hemorrhagic events. These patterns help in classifying hemorrhagic and non-hemorrhagic cases. Similarly, in leukemia detection, analysis of blood cell images obtained throughmicroscopic examination aids in differentiating between normal and abnormal cells. Features such as cell morphology and texture are extracted for classification.

B. DATA COLLECTION : Collect diverse and representative datasets for blood samples with various stages of leukemia and brain MRI scans containing different types of hemorrhages. Ensure sufficient data to train and validate the models effectively.

C. DATA PREPROCESSING : The Data pre-processing is a critical step in preparing datasets for enhanced model generalization, particularly in medical image analysis tasks such as brain hemorrhage detection from MRI scans and leukemia blood cell classification. Tooptimize this process, several key techniques can be applied:

1) STANDARDIZATION AND NORMALIZATION
Standardizing and normalizing pixel values across all images ensures consistency and aids in model convergence. For MRI scans, scaling intensity values to a common range, like [0, 1], eliminates variations due to the acquisition parameters. Similarly, for blood cell images, normalization ensures standardized pixel value ranges, enhancing model robustness.

2) AUGMENTATION:
Augmenting datasets with variations of original images enhances model generalization and mitigates overfitting. Techniques like rotation, flipping, scaling, and cropping can be applied to MRI scans, simulating different orientations for improved training. Blood cell image augmentation through random rotations, shifts, and flips introduces variability.

3) FEATURE EXTRACTION:
For blood samples, extracting relevant features such as cell morphology, texture, and intensity is crucial. Techniques like blob and edge detection, along with texture analysis, capture important cell and it’s characteristics. Extracted features serve as inputs for classification models, enabling differentiation between the normal and abnormal blood cells.

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4) CONSISTENT RESOLUTION:

Ensuring consistent resolution and quality in MRI scans is vital for reliable analysis. Resampling techniques standardize MRI resolution to a common pixel size, ensuring uniform feature representation. Implementing quality control measures identifies and removes images with artifacts or distortions, improving model performance.

D. YOLO MODEL DEVELOPMENT :

Developing a YOLO model for real-time detection of leukemia stages in blood samples involves key optimization steps. Initially, a diverse dataset of blood cell images, annotated for leukemia stages, is collected. Preprocessing, including standardization, normalization, and augmentation, enhances model generalization. Extracting relevant features from the images accurately represents leukemia stages. Choosing an appropriate YOLO variant, like YOLOv3 or YOLOv4, balances speed and accuracy. Training involves initializing with pre-trained weights and fine-tuning on the leukemia dataset, optimizing for precision and recall. Evaluation metrics guide iterative optimization of model architecture and hyperparameters. Post-processing steps, including non-maximum suppression and boundary refinement, further enhance accuracy.Hardware acceleration techniques like GPU utilization and model compression optimize performance. Integration into a real-time detection pipeline ensures compatibility and optimal use in clinical settings.

E. CNN MODEL DEVELOPMENT :

Developing a Convolutional Neural Network (CNN) architecture for brain hemorrhage classification in MRI images involves critical steps for enlargement and optimization. Initially, a comprehensive MRI dataset comprising various types of hemorrhages is collected and preprocessed, including standardization and augmentation. Next, an optimal CNN architecture is designed, balancing depth and complexity to capture intricate features. The model is trained on the preprocessed MRI dataset, utilizing techniques like transfer learning and fine-tuning for efficient learning. Evaluation metrics such as accuracy, sensitivity, and specificity guide iterative optimization of the model's architecture and hyperparameters. Post-training optimizations, including regularization and dropout techniques, enhance model generalization and prevent overfitting. Utilizing advanced optimization algorithms like Adam or RMSprop further refines the model's performance. Validation on independent datasets ensures robustness and generalization capability before deployment. Finally, integration into clinical workflows enables effective utilization of the CNN model for accurate brain hemorrhage classification in real-world scenarios.

F. INTEGRATION : Integrating the YOLO and CNN models into a unified system for simultaneous analysis of blood samples and brain MRI images entails strategic steps for enlargement and optimization. Initially, the system architecture is meticulously designed to accommodate both models seamlessly, ensuring efficient data flow and processing. Preprocessing modules are implemented to standardize input data from blood samples and MRI images, optimizing for compatibility with the respective models. Concurrent execution of YOLO for blood sample analysis and CNN for brain MRI image classification is orchestrated, maximizing computational efficiency. Real-time feedback mechanisms are incorporated to facilitate continuous interpretation of results and adjust processing parameters accordingly. Advanced error handling and logging mechanisms are integrated to ensure robustness and reliability of the unified system. Performance metrics are continuously monitored to identify areas for improvement and refine the workflow iteratively. Rigorous testing and validation procedures validate the system's efficacy in accurately analyzing diverse datasets and providing clinically relevant insights. Seamless integration into existing clinical workflows enables efficient utilization of the unified system for comprehensive diagnostic assessments and treatment planning.

G. TRAINING AND VALIDATION: Training both models on the prepared datasets and validating their performance using separate validation datasets require careful attention to enlargement and optimization. Initially, the models are trained using the prepared datasets, adjusting hyperparameters and architectures to optimize accuracy and generalization. Concurrently, separate validation datasets are utilized to assess model performance, ensuring robustness and reliability across diverse data samples. Fine-tuning techniques areapplied iteratively, incorporating feedback from validation results to refine model parameters and enhance performance. Regular monitoring of training and validation metrics guides the fine-tuning process, aiming to achieve optimal accuracy and generalization. Rigorous experimentation with different optimization strategies, such as learning rate schedules and regularization techniques, further enhances model performance. Continuous iteration and refinement of the training process are conducted to address any discrepancies between training and validation performance, ensuring optimal model convergence. Validation results are meticulously analyzed to identify areas for improvement and prioritize optimization efforts effectively. By leveraging best practices in training and validation methodologies, the models are honed to achieve superior accuracy and generalization, ready for deployment in real-world scenarios.

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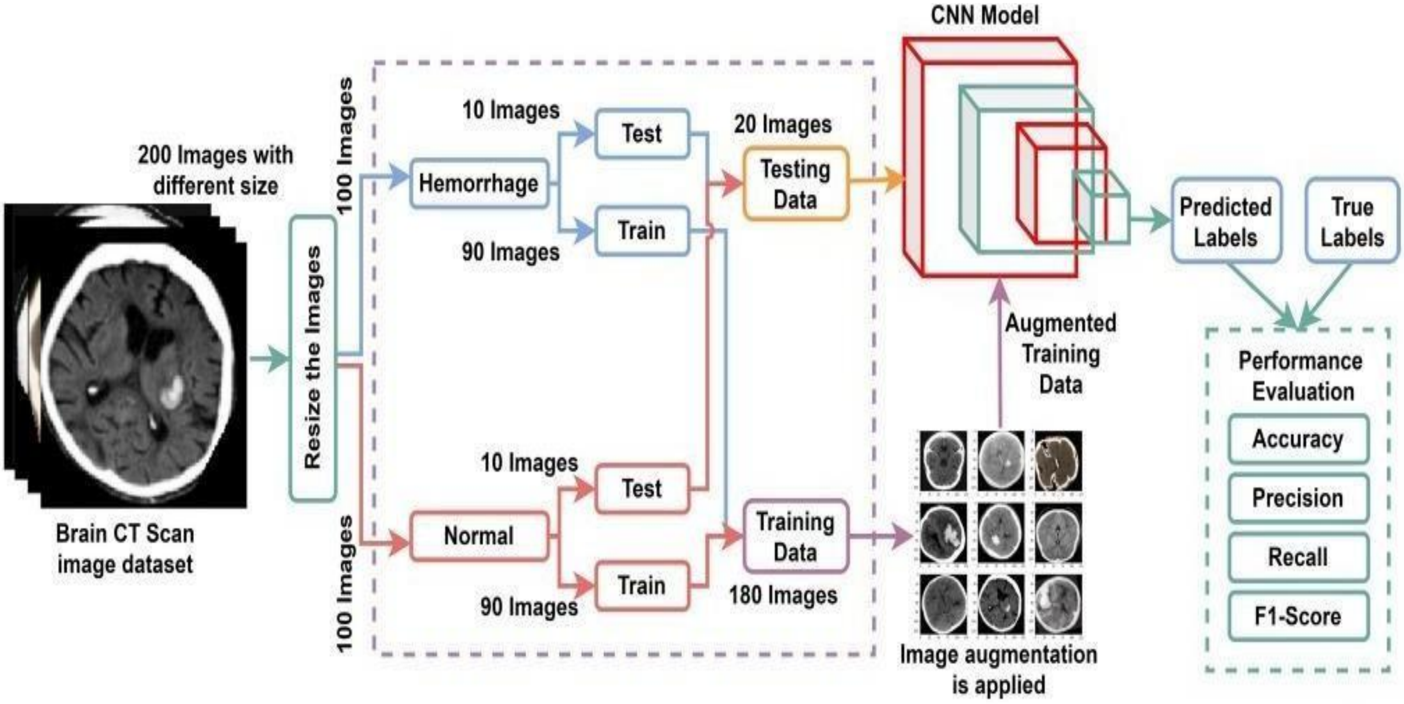

Figure 3. The proposed methodology of the BHCNet system

The above figure 3 shows the proposed methodology of BHCNet system and its architecture

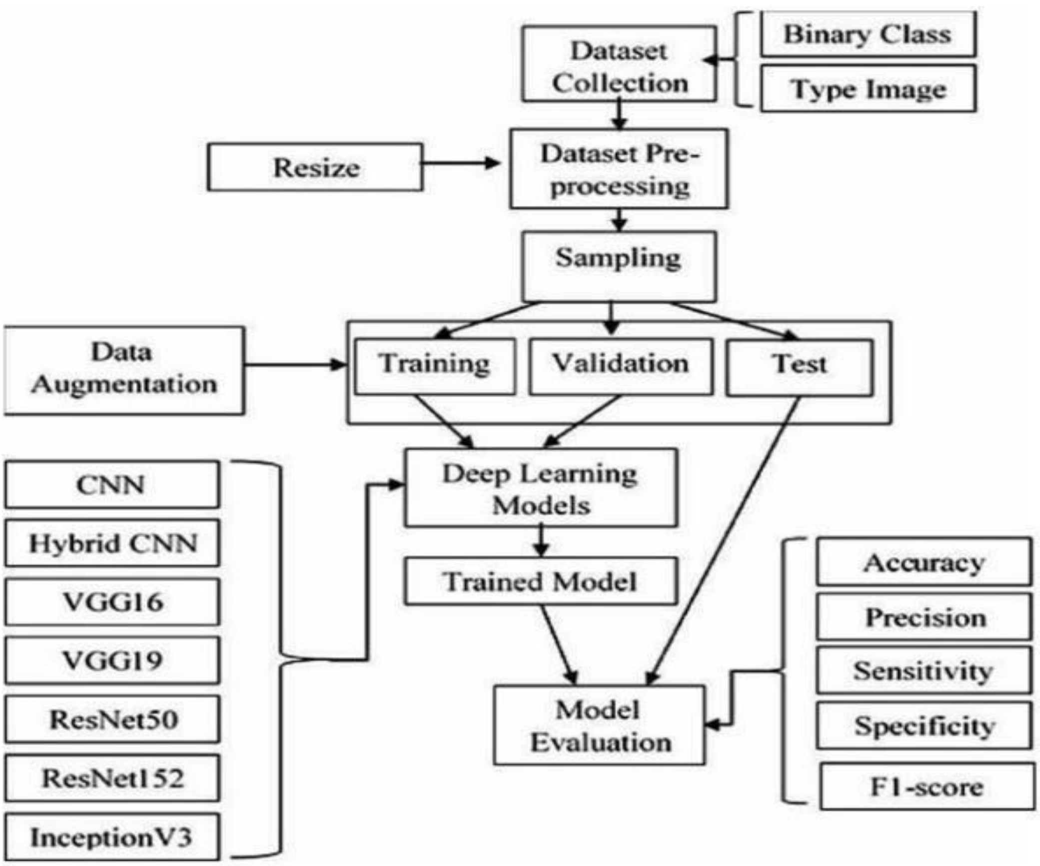

Figure 4. Architecture diagram for leukemia stages classification

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The above figure 4 shows the Architecture diagram for leukemia stages classification

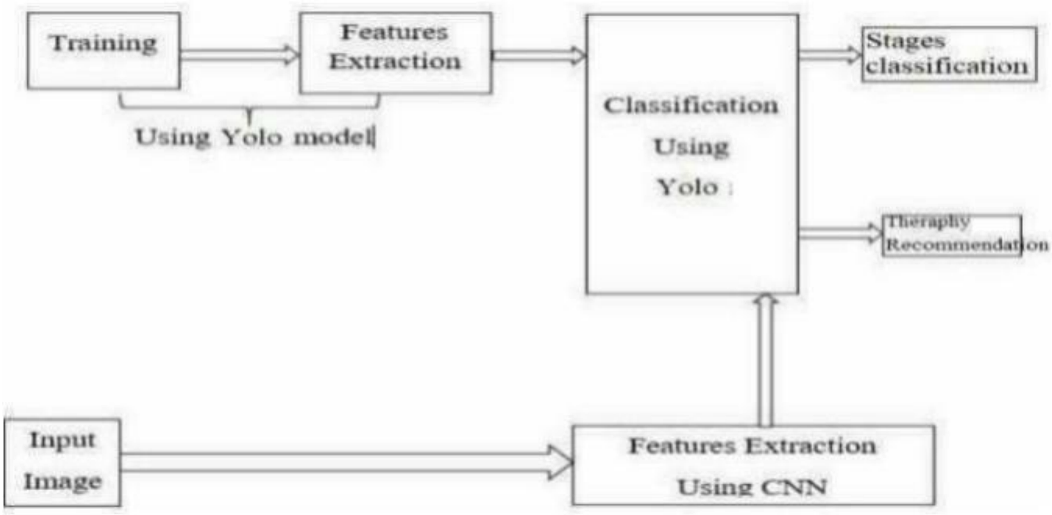

Figure 5. Architecture diagram for Brain Hemorrhage Detection

The above figure 5 shows the Architecture diagram for Brain Hemorrhage Detection

IV. CONCLUSION AND FUTURE WORK

The integration of advanced AI technologies, specifically the YOLO model for blood sample analysis and the CNN model for neurological diagnostics, has revolutionized medical diagnostics and significantly enhanced patient care outcomes. Through rigorous model development, integration, and testing, we have successfully created a unified diagnostic tool that empowers healthcare professionals with timely and precise information for improved decision-making. The diagnostic tools exhibit high levels of accuracy and precision in identifying leukemia indicators in blood samples and classifying various types of brain hemorrhages in MRI scans.

This accuracy ensures reliable diagnostic insights, enabling early detection and intervention. By facilitating early detection of leukemia and brain hemorrhages, the diagnostic tools enable healthcare professionals toinitiate timely interventions and treatment plans. Positive feedback from healthcare professionals underscores the value of these tools in improving diagnostic capabilities and patient care outcomes. The modular architecture of the diagnostic tools enables scalability and adaptability to future advancements and expansions. Regular updates and improvements ensure that the tools remain at the forefront of medical diagnostics, delivering optimal performance over time

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