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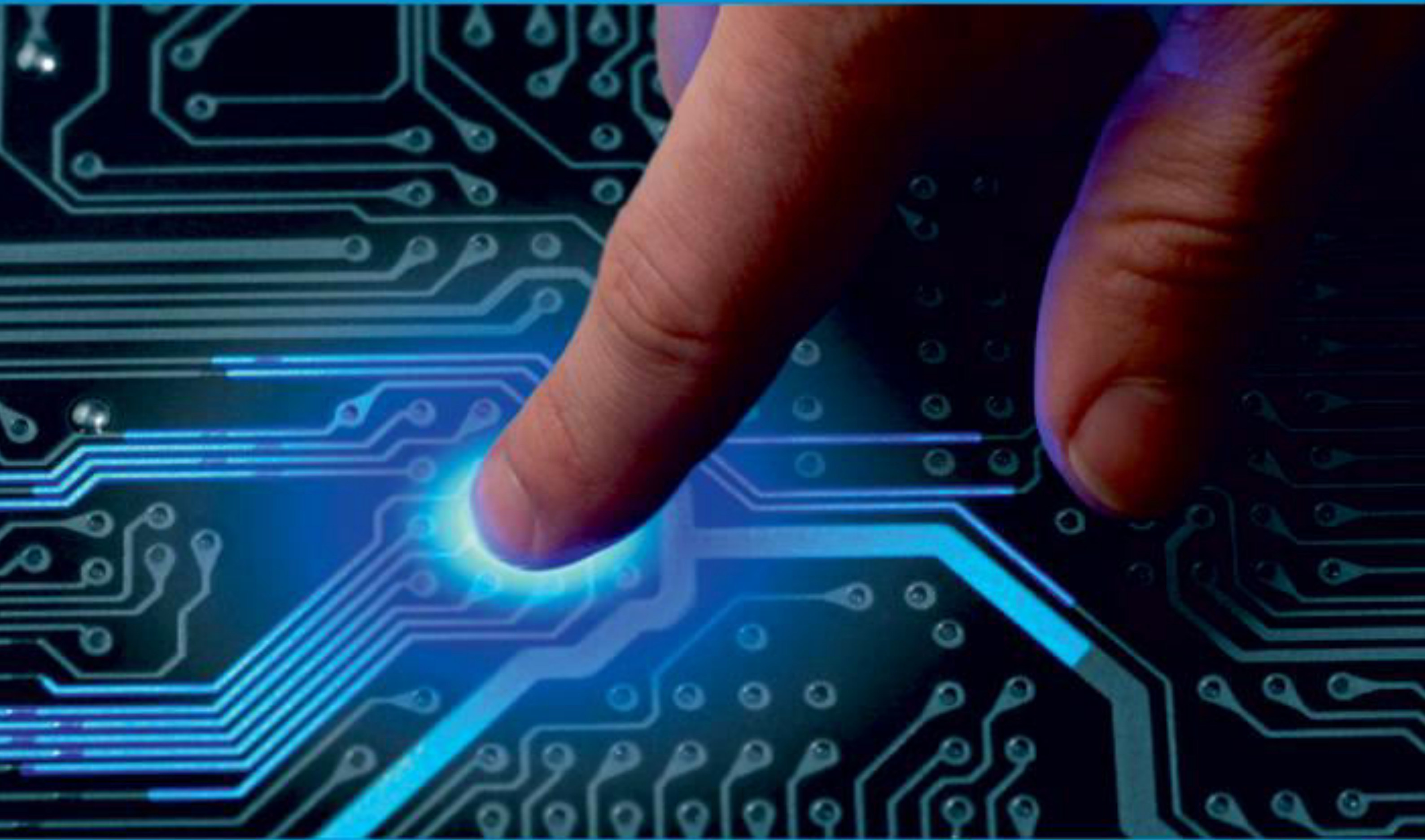

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Early Detection of Cancer Using Artificial Intelligence

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ABSTRACT: Cancer is a global health concern, and early detection plays a crucial role in improving patient outcomes and reducing mortality rates. In recent years, artificial intelligence (AI) techniques have emerged as promising tools for early cancer detection. This systematic review aims to provide an overview of the current state of research on using AI for early detection of cancer. The review begins by presenting an overview of the various types of cancers and their diagnostic challenges. It then delves into the potential of AI in cancer detection, discussing different AI techniques such as machine learning, deep learning, and image analysis. The review also examines the sources of data used in AI-based cancer detection, including medical images, genomic data, electronic health records, and other clinical data. Furthermore, the review highlights the significant advancements made in AI-based cancer detection across different cancer types, such as breast, lung, prostate, colorectal, and skin cancer. It discusses the specific algorithms and models developed for each cancer type and their performance in terms of sensitivity, specificity, and accuracy. The review also addresses the challenges and limitations associated with AI-based cancer detection, including data availability, standardization, interpretability, and regulatory aspects. Moreover, it explores the ethical considerations and potential biases that may arise in implementing AI systems for cancer detection. Lastly, the review discusses the future directions and potential implications of AI in early cancer detection. It emphasizes the need for large-scale clinical trials and collaborations between healthcare professionals, researchers, and AI experts to validate and implement AI models in clinical practice.

KEYWORDS: Patient; cancer; Healthcare professionals; Health records; Clinical data.

I. INTRODUCTION

Cancer is a leading cause of morbidity and mortality worldwide, posing a significant challenge to public health. Early detection of cancer is critical for improving patient outcomes, as it allows for timely intervention and treatment. However, traditional cancer detection methods often rely on invasive procedures or are limited by human error and subjectivity. In recent years, artificial intelligence (AI) has emerged as a powerful tool that has the potential to revolutionize cancer detection and diagnosis.

AI encompasses a range of computational techniques that enable machines to learn from and analyze large amounts of data, identify patterns, and make accurate predictions. Machine learning, a subset of AI, involves the development of algorithms and models that can automatically learn and improve from experience without being explicitly programmed. Deep learning, a specialized form of machine learning, utilizes artificial neural networks to extract complex features from data and has shown remarkable success in various domains, including image recognition and natural language processing.

The application of AI in cancer detection holds immense promise. By leveraging AI techniques, healthcare professionals can harness the power of large-scale data sets, including medical images, genomic data, electronic health records, and clinical data, to develop accurate and efficient cancer detection models. These models can aid in the early identification of cancer, distinguishing between benign and malignant lesions, and predicting patient outcomes.

II. RELATED WORK

Breast Cancer Detection: AI-based approaches have shown promise in improving breast cancer detection using mammograms. Studies have explored the application of deep learning algorithms for mammogram analysis, achieving high sensitivity and specificity. Additionally, AI models have been developed to predict breast cancer risk based on patient demographic data and genetic information.

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Lung Cancer Detection: AI has been utilized to detect lung cancer in medical imaging, such as chest X-rays and CT scans. Deep learning models have demonstrated the ability to identify suspicious lung nodules and classify them as benign or malignant. These models have shown promising results in assisting radiologists in early detection and diagnosis of lung cancer.

Prostate Cancer Diagnosis: AI techniques have been employed to enhance the accuracy of prostate cancer diagnosis. Machine learning algorithms have been trained on multiparametric magnetic resonance imaging (MPMRI) data to detect and classify prostate cancer lesions. These models have demonstrated improved diagnostic performance and have the potential to guide targeted biopsies.

Colorectal Cancer Screening: AI has been applied to colonoscopy images and pathology slides for the detection of colorectal cancer. Deep learning algorithms have been developed to identify polyps and adenomas, which are precursors to colorectal cancer. AI-based systems have shown promising results in increasing the detection rate of clinically significant lesions during colonoscopy examinations.

Skin Cancer Detection: AI has been employed in the early detection of skin cancer through analysis of meatoscopic images. Deep learning models have been trained to distinguish between benign and malignant skin lesions, achieving high accuracy rates. These AI systems have the potential to assist dermatologists in triaging skin lesions and determining the need for further investigation.

III. PROPOSED ALGORITHM

Convolutional Neural Network

Convolutional Neural Network is one of the main categories to do image classification and image recognition in neural networks. Scene labelling, objects detections, and face recognition, etc., are some of the areas where convolutional neural networks are widely used.

CNN takes an image as input, which is classified and process under a certain category such as dog, cat, lion, tiger, etc. The computer sees an image as an array of pixels and depends on the resolution of the image. Based on image resolution, it will see as **h * w * d**, where h=height w=width and d= dimension. For example, An RGB image is **6 * 6 * 3** array of the matrix, and the grayscale image is **4 * 4 * 1** array of the matrix.

In CNN, each input image will pass through a sequence of convolution layers along with pooling, fully connected layers, filters (Also known as kernels). After that, we will apply the Soft-max function to classify an object with probabilistic values 0 and 1.

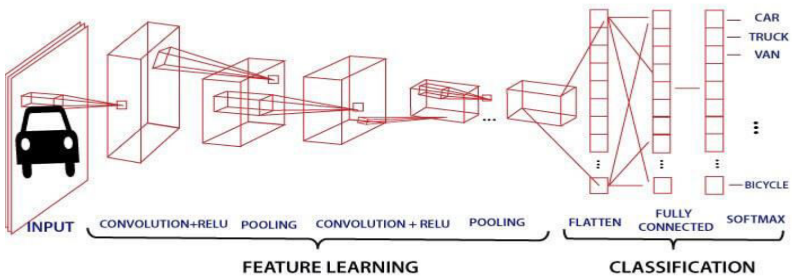

FIG. RELATED CNN ALGORITHM

Convolution Layer

Convolution layer is the first layer to extract features from an input image. By learning image features using a small square of input data, the convolutional layer preserves the relationship between pixels. It is a mathematical operation which takes two inputs such as image matrix and a kernel or filter.

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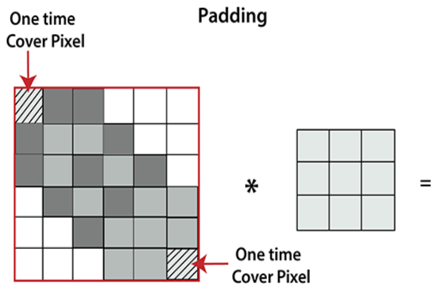
Strides

Stride is the number of pixels which are shift over the input matrix. When the stride is equalled to 1, then we move the filters to 1 pixel at a time and similarly, if the stride is equalled to 2, then we move the filters to 2 pixels at a time. The following figure shows that the convolution would work with a stride of 2.

Padding

Padding plays a crucial role in building the convolutional neural network. If the image will get shrink and if we will take a neural network with 100's of layers on it, it will give us a small image after filtered in the end.



It is clear from the above picture that the pixel in the corner will only get covers one time, but the middle pixel will get covered more than once. It means that we have more information on that middle pixel, so there are two downsides:

- Shrinking outputs
- Losing information on the corner of the image.

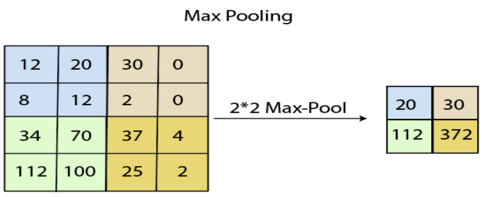
Pooling Layer

Pooling layer plays an important role in pre-processing of an image. Pooling layer reduces the number of parameters when the images are too large. Pooling is "downscaling" of the image obtained from the previous layers. It can be compared to shrinking an image to reduce its pixel density. Spatial pooling is also called down sampling or subsampling,

Max Pooling

Max pooling is a sample-based discretization process. Its main objective is to downscale an input representation, reducing its dimensionality and allowing for the assumption to be made about features contained in the sub-region binned.

Max pooling is done by applying a max filter to non-overlapping sub-regions of the initial representation.



IV. PSEUDO CODE

Step 1: Start
Step 2: Open application
Step 3: View Dataset
Step 4: Upload Histopathological Images Dataset
Step 5: Ad Hoc Network of 5 Nodes .
Step 6: Energy Consumption by Each Node
Step 7: Accuracy comparison
Step 8: Stop

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V. SIMULATION RESULTS

This project we are implementing Artificial Intelligence algorithm called as Neural Networks with various optimizer techniques such as ADAM, SGD and Gradient Descent Mini Batch to predict cancer disease.
showed in

Fig 1. see dataset contains 3 different types of cancers and just go inside any folder to view those images.

Fig. 2 Upload Histopathological Images Dataset.

Fig .3 we can see dataset contains 555 images and then showing train and test data size and in graph x-axis represents 'Cancer' type and y-axis represents.

Fig. 4. screen AI with ADAM got 92% accuracy and in confusion matrix graph x-axis represents Predicted Labels and y-axis represents TRUE labels and different colour boxes represents CORRECT Prediction count and same blue colour boxes represents incorrect prediction count.

Fig. 5. above screen with Mini Batch also we got 51% accuracy.

Fig. 6 screen we can see all algorithm performance in tabular and graphical format and in all algorithms 'AI with ADAM' got high performance or accuracy.

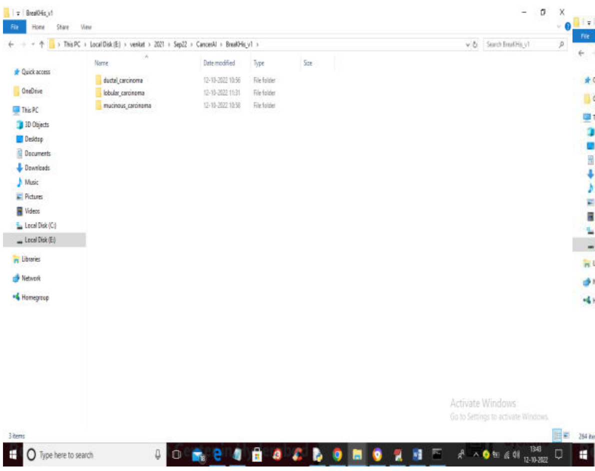

Fig.1. View Dataset

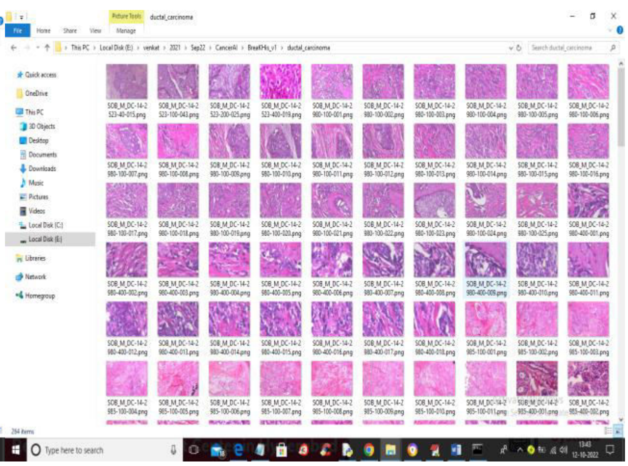

Fig. 2. Upload Histopathological Images Dataset

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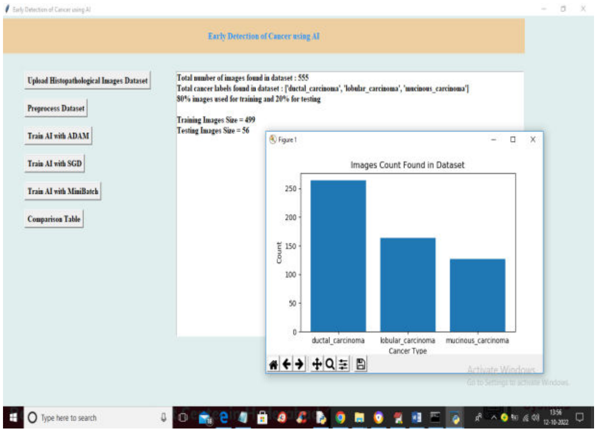


Fig. 3. Ad Hoc Network of 5 Nodes

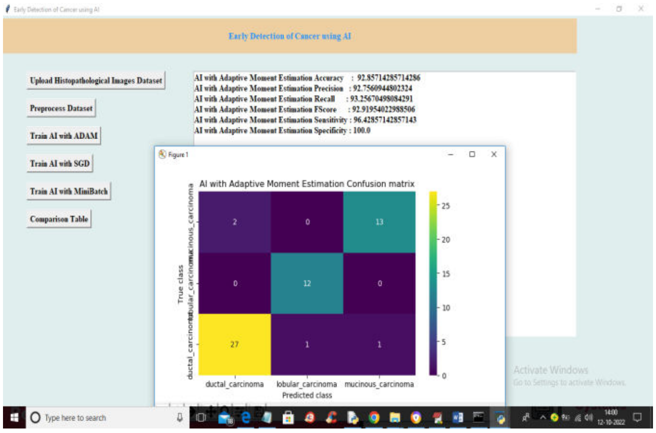
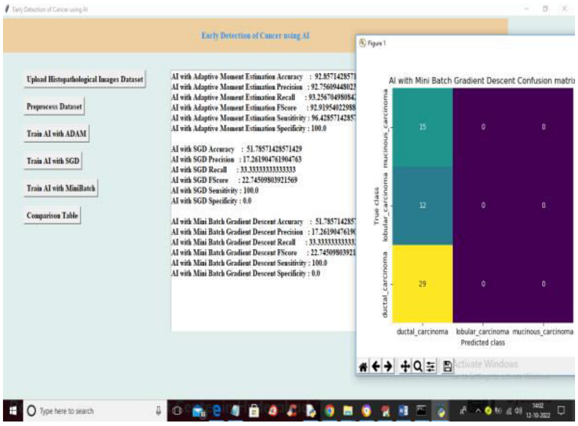


Fig 4. Energy Consumption by Each Node



VI. Conclusion and Future Work

The simulation results showed Early detection of cancer is crucial for improving patient outcomes and reducing mortality rates associated with the disease. Artificial intelligence (AI) has emerged as a powerful tool in the field of cancer detection, offering the potential to enhance accuracy, efficiency, and accessibility.

Through the integration of AI techniques, such as machine learning and deep learning, with diverse data sources including medical images, genomic data, and clinical records, AI-based systems have shown promise in various aspects of early cancer detection. These include improved diagnostic accuracy, risk assessment, personalized treatment planning, and optimization of screening programs.

However, the successful implementation of AI in early cancer detection requires addressing challenges and constraints. These include data availability and quality, interpretability of AI algorithms, regulatory compliance, validation and clinical implementation, cost considerations, algorithm bias, and integration with existing healthcare systems. Overcoming these challenges necessitates collaboration among researchers, healthcare professionals, regulators, and policymakers.

Despite the constraints, the potential benefits of AI in early cancer detection are substantial. AI systems can assist healthcare professionals in accurate diagnosis, treatment selection, and prognosis prediction, ultimately leading to improved patient outcomes. Moreover, AI can optimize cancer screening programs, enhance efficiency, and enable personalized medicine Moving forward, continued research, validation studies, and advancements in AI techniques are essential for the successful integration of AI into routine clinical care. Additionally, ensuring ethical considerations, data privacy, and regulatory compliance will be critical in maintaining trust and acceptance of AI-driven cancer detection systems.

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