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ADVANCING HISTOPATHOLOGIC CANCER DETECTION USING DIVERSE CNN ARCHITECTURES AND TRANSFER LEARNING

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ABSTRACT

Histopathologic cancer detection plays a crucial role in early diagnosis and treatment planning. This research explores the application of distinct convolutional neural network (CNN) architectures, including VGG, InceptionV3, ResNet50, DenseNet121, and a custom CNN, for improving histopathologic cancer detection through transfer learning and advanced data augmentation techniques. Cancer Detection dataset is collected from Kaggle serves as the foundation for experiments. Transfer learning is employed from general image datasets like ImageNet and medical imaging datasets, tailoring the models to histopathologic characteristics. Each CNN architecture is examined independently to understand its unique contribution to feature extraction. Advanced data augmentation strategies, carefully designed to address limited annotated data, enhance the generalization capabilities of each model. These strategies, including rotation, shift, shear, and zoom, contribute to improved performance in histopathologic cancer detection. The work presents comprehensive analyses of each model's performance metrics, providing insights into their strengths in capturing intricate histological patterns. Results showcase the effectiveness of the individual CNN architectures, each demonstrating superior performance metrics. The findings underscore the significance of selecting appropriate architectures for specific tasks, contributing to advancements in automated histopathologic analysis with potential applications in early cancer diagnosis and treatment planning.

Keywords: *Histopathologic Cancer, CNN, Transfer Learning, VGG, Resnet, Inception*

1. INTRODUCTION

Cancer, a complex spectrum of diseases characterized by the uncontrollable proliferation and dissemination of abnormal cells, continues to pose a significant global health challenge. Despite considerable advancements in medical science, the timely and precise identification of cancerous tissues remains paramount for achieving successful treatment outcomes. Central to cancer diagnosis, histopathologic examination entails the microscopic scrutiny of tissue samples to discern cellular abnormalities and pathological changes.

Histopathologic cancer detection plays an incomparable role in the field of oncology, providing invaluable insights into the nature, grade, and extent of malignancies. Through a meticulous analysis of cellular morphology, tissue architecture, and the presence of specific biomarkers, pathologists can categorize tumors, assess their aggressiveness, and formulate personalized treatment strategies. This detailed examination not only serves to confirm or refute clinical suspicions but also holds a pivotal position in the staging process, prognosis determination, and therapeutic decision-making.

Improving cancer detection methods using histopathology is crucial. The development of tailored medicines and precision medicine techniques relies heavily on the timely and precise detection of malignant tissues. This, in turn, improves patient outcomes via early intervention. In addition, the possibility of automating part of the histopathologic analysis process helps with problems associated with a lack of qualified pathologists, which is particularly true in areas with limited resources. Enhancing histopathologic cancer diagnosis has been revolutionized in recent years by integrating AI and DL techniques, including CNNs. The possibility to enhance human pathologists' skills is propelling this paradigm shift toward faster and more accurate interpretation of massive volumes of histology data.

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2. LITERATURE SURVEY

Using ML and DL for health sector is not a new era. In [1], the authors developed ML models to identify minor alterations in breast tissue that could signal cancer, even prior to such changes being evident on a mammogram, as traditionally practiced. This underscores the critical need for advanced diagnostic tools that can detect cancer at its earliest stages, thus improving patient outcomes. However, the research highlighted the necessity for further exploration to tackle the constraints and challenges linked with ML in diagnosing breast cancer, along with the establishment of consistent protocols for gathering and analyzing data. PRISMA was used to assess and analyze a meta-analysis in [2]. Study eligibility and quality were assessed for 98 publications after searching and screening. The review concluded that CNN was the most accurate and extensively used breast cancer detection model, emphasizing the need for continuous improvement and validation of these models to enhance diagnostic precision in real-world settings. The research also examined deep learning model problems and future research paths in breast cancer detection to inform researchers and practitioners.

DL-based approaches were presented by [3] to help dermatologists improve accuracy and early detection. Recently published deep learning skin cancer categorization studies were evaluated in this study. The study included the most popular DL models and datasets for skin cancer categorization. In [4], transfer learning was used in DL models to identify breast cancer on histopathology pictures. The study's findings are that Resnet and DenseNet are high-performing models highlight the significance of leveraging transfer learning for improved diagnostic accuracy, thereby justifying further research in this direction. In [5], authors reviewed ML for cancer diagnosis, focusing on lung, breast, prostate, and colorectal cancers. They used SBERT (2019) and SimCSE (2021) transformers to develop a technique relying on raw DNA sequences from tumor/normal pairs. SBERT and SimCSE representations were employed in XGBoost, RF, LightGBM, and CNNs for classification. The novelty of applying these transformers to represent DNA sequences in cancer diagnosis underscores the potential for innovative approaches to enhance diagnostic methodologies. The authors in [6] suggested reconstructing pictures using a Variational and Denoising Autoencoder, then utilizing a CNN model to predict cancerous or non-cancerous input images. This approach presents a novel perspective in combining generative modeling with CNNs, which could lead to significant advancements in diagnostic accuracy.

Histopathology images can be used to diagnose breast cancer early using DL [7]. An image public breast histopathology imaging database was used to test the method's robustness. A DL model for feature extraction, a unique feature selection framework, and ML algorithms to categorize breast cancer into IDC and normal classes were used for automated diagnosis. The experimental results showing 93% accuracy underscore the potential of DL models to assist pathologists in early and accurate diagnosis, which is crucial for effective treatment planning. In [8], the authors suggested an ML and image processing-based cancer detection and classification system. The system has two basic processes: preprocessing to discover characteristics and discrimination to differentiate benign from malignant lung cancer. This bifurcated approach highlights the need for robust preprocessing techniques to enhance the accuracy of ML models in cancer detection. [9] described an ML-based cancer detection model that predicted cancer stages and kinds using patient data. The model was trained on a huge dataset of patient records using DT, RF, and XG Boost methods to achieve excellent accuracy and sensitivity. The findings showed that ML-based cancer diagnosis might save lives. Clinicians might use the model to make better patient care choices. Pathologists may have profited from the aid of an automated diagnostic system in order to improve their efficiency, as stated by [10]. In order to determine specific instances of breast cancer, the Naive Bayes approach was used. This study illustrates the importance of employing ML techniques in early detection and the potential impact on healthcare planning and patient management.

Deep learning-based CNN feature extraction and classification was advocated in [11]. Using the LC25000 Lung histopathologic image collection, the research assessed its very accurate lung and colon cancer detection. There were parameter and accuracy comparisons with other image analysis algorithms. Using the EfficientNet method might improve cancer diagnosis and aid in the expansion of more operative treatments. For lung cancer detection, [12] offered an adapted lightweight end-to-end DL technique using CNN. The methodology's given good accuracy in histopathological image classification signifies the potential of lightweight models in real-time clinical applications, highlighting the need for further exploration and optimization of such models. A collection of colon cancer histological pictures with

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the same dimensions was used in [13]. Using CNN to interpret difficult data, a deep learning algorithm predicted CRC cancers from histopathology pictures. CNN might detect aberrant tumor patterns. The model was a five-layer deep neural network with input, four hidden, and output layers. The hidden layer employed ReLU activation and the output layer Softmax. The deep learning model given good results. This study's high accuracy highlights the effectiveness of CNNs in cancer detection and the need to incorporate deep learning models into diagnostic frameworks.

A multi-instance categorization Network (MICNet) with visual explanation mechanisms for histological breast cancer image categorization was proposed in [14]. A simple two-dimensional convolution kernel generated visual explanation maps using VGG11 model characteristics pre-trained on ImageNet. Mirror padding and overlap cropping improved classification performance using Multiple Instance Learning (MIL). To enhance visual explanations, weighted average pooling was used. On BreakHis and Camelyon16 patch-based datasets, MICNet beat other CNN models in classification and gave clear visual explanations for its results. The provision of visual explanations for model predictions is crucial for clinical adoption, as it builds trust and transparency in AI-based diagnostic tools. In [15], the authors used AI to autonomously diagnose and categorize lung cancer, relieving pathologists of their workloads. The model classified cancer pictures into malignant and benign, which was advantageous to the medical business, particularly in areas without pathology centers. The ultimate objective was to compare benign and malignant cancer cells to help grade cancer without a pathologist. This study emphasizes the potential of AI in augmenting diagnostic capabilities, particularly in resource-constrained settings, underscoring the significance of this research. [16] compared CNN and transfer learning-based DenseNet121 deep learning models for automated breast histopathology image categorization into cancerous or benign categories. The research examined how picture magnification, scaling, and rotation affected model accuracy in histopathology images of both kinds. DenseNet performed well in some settings, and transfer learning improved training accuracy. The review in [17] provided a concise overview of how ML & DL were applied in routine healthcare tasks, addressing both obstacles and opportunities in the use of AI for tumor morphology. WPBC and UCI ML databases were used to assess the suggested techniques, which included RF and DT to find significant breast cancer biomarkers. The higher sensitivity and specificity achieved through these techniques highlight the potential for improved diagnostic tools, justifying the need for continuous research in this area. In [18], AI-powered medical diagnostic systems were developed to identify cancer cells in histopathology pictures. AI-assisted pathologists correctly identified malignancies using labeled pictures. To recognize and categorize abnormal cells, the technique blended image processing and DL. Despite limitations in tumor size and location, AI-based systems provided fast and accurate cancer diagnosis, improving treatment outcomes.

The work in [19] focused on flexibility to varied picture kinds, information relevance, efficient performance, and managing sparse cancer cells to address breast cancer image classification problems. OLGV3 Net Classifier used upgraded Inception V3 for visual understanding and LightGBM for accurate classifications. The study obtained high accuracy by fine-tuning the model's parameters using Sequential Model-Based Optimization (SMBO). [20] automated the classification of microscopic histological images into benign, in situ, aggressive, and normal breast cancer groupings. Image enhancement, segmentation, feature extraction, selection, and classification were recommended. Comparing clustering and Otsu's global thresholding segmentation techniques. After segmenting images using K-means and Global thresholding, morphological and textural features were obtained. PCA selected characteristics. The paper concluded by comparing K-means and Global thresholding methods with different classifiers. Global thresholding improved. [21] suggested employing deep CNNs, Inception_V3 and Inception_ ResNet_V2 with transfer learning to analyze histological breast cancer pictures. The networks were optimized for binary or multi-class classification. Experimental findings showed that Inception_ResNet_V2 was better for this analysis than Inception_V3.

In [22], a proportional analysis of advanced segmentation methods applied. They conducted for extracting cancerous cells in histopathological images using the Breast Cancer dataset. The experimental results were analyzed. Based on histological pictures, [23] classified breast cancer as benign or malignant using an open-source dataset. The system analyzes hematoxylin and eosin-stained breast biopsy pictures using the Keras library and DL CNN. In [24], the authors applied DL models for cancer detection and reported reasonable results. In [25], a Deep CGAN balanced normal and

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cancerous pictures before data augmentation. The DenseNet pre-trained model classified breast cancer using block-concatenated features. We collected features from lower layers using global average pooling, and the model had good test accuracies at varied magnifications. The findings show that the breast cancer picture categorization system works.

In summary, the reviewed literature highlights the critical need for advanced diagnostic tools leveraging ML and DL to enhance early cancer detection and diagnosis. This research contributes significantly by addressing the limitations and challenges identified in previous studies, proposing innovative approaches for improved diagnostic accuracy and reliability. The ongoing advancements and the need for robust, efficient, and transparent AI-based diagnostic tools justify the necessity and significance of this research.

While many previous works have relied on standard ML or DL models for predicting cancer, this paper presents a novel approach that uses transfer learning and CNN methodologies for enhanced accuracy. The paper is structured as follows: Section 3 delves into the proposed method, Section 4 showcases the results and accompanying discussion, and Section 5 concludes the findings.

3. METHODOLOGY

The proposed architecture for cancer detection shown in Figure 1. Histopathologic cancer detection is a critical component in the early diagnosis and treatment planning of cancer. In this research, we present a comprehensive exploration of distinct Convolutional Neural Network (CNN) architecture VGG19, InceptionV3, ResNet50, DenseNet121, and a custom-designed CNN.

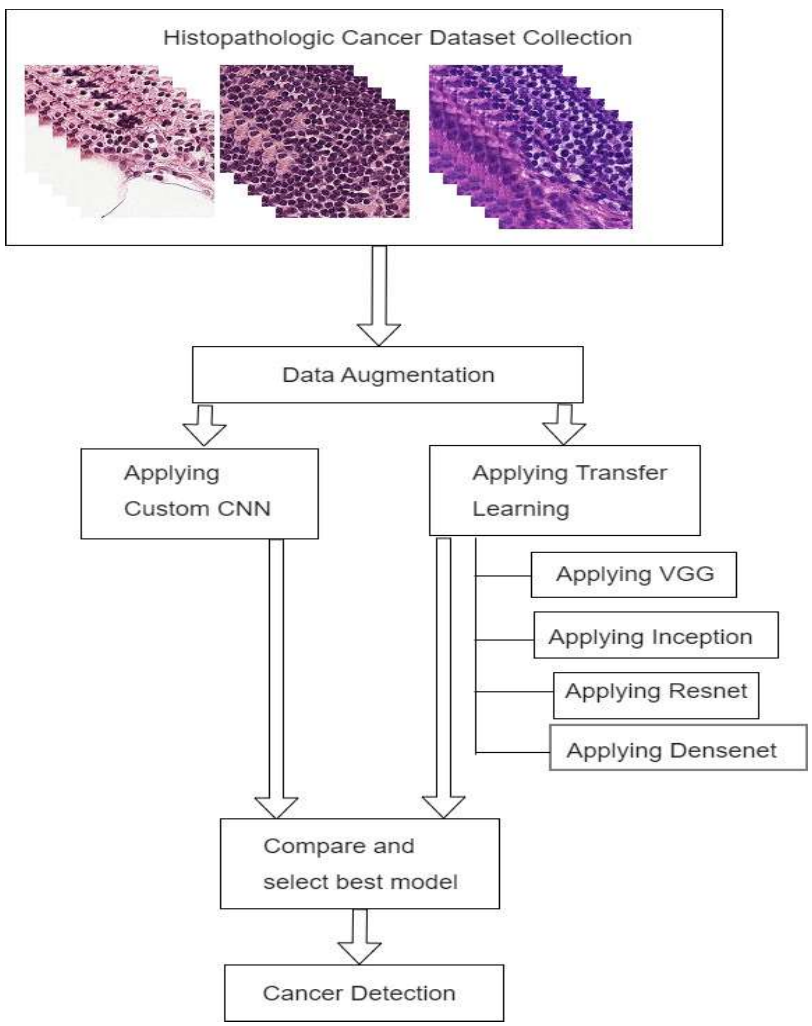

Figure 1. Proposed Method for Cancer detection

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Our primary objective is to enhance histopathologic cancer detection through the strategic application of transfer learning and advanced data augmentation techniques.

3.1 Dataset Used

The dataset of Histopathologic Cancer Detection is downloaded from Kaggle [26]. Comprising histopathologic images sourced from lymph node sections, the dataset captures microscopic perspectives of tissues from different body regions like the neck, armpits, chest, abdomen, and groin. With an extensive collection of color images, this dataset presents a demanding challenge in image classification. Each image is meticulously labeled with binary annotations, marking the presence or absence of metastatic tissue within the analyzed lymph node sections. The dataset's significance is highlighted by the presence of metastatic tissue, indicating the spread of cancer cells from the primary tumor to other parts of the body, offering crucial insights into advanced stages of cancer.

3.2 Transfer Learning

Transfer learning was a pivotal strategy used in our technique. To adjust the CNN models to the unique properties inherent in histopathologic images, we utilized pre-existing information from general image datasets like ImageNet and specialized medical imaging datasets. The VGG19, InceptionV3, ResNet50, DenseNet121, and a customized CNN architectures were all evaluated separately. The objective in conducting this investigation was to better understand the efficacy of each architecture in histopathologic cancer diagnosis by elucidating its distinct contributions to feature extraction.

3.2.1 VGG19

The architecture of VGG19 is simple and homogeneous. It has 19 layers—16 convolutional and 3 fully linked. The whole VGG19 network employs modest 3x3 convolutional filters. It uses max-pooling layers to reduce input spatial dimensions. Fully linked layers help extract high-level features. VGG19, with its deep architecture and use of small convolutional filters, has already learned generic features from a diverse dataset like ImageNet. By leveraging this pre-trained knowledge, the model can quickly adapt to histopathologic images, enabling effective feature extraction. The transfer of learned representations from VGG19 facilitates faster convergence during training on the cancer detection dataset, especially when the annotated data is limited

3.2.2 Inception V3

InceptionV3 optimizes convolutional layer filter sizes using Inception modules, which employ multiple filter sizes concurrently. Inception Modules concatenate convolutional layer outputs with different filter sizes to capture characteristics at different scales. Training using auxiliary classifiers in InceptionV3 reduces the vanishing gradient issue. InceptionV3, with its inception modules and simultaneous use of multiple filter sizes, offers a unique advantage in capturing diverse features within histopathologic images. Transfer learning from InceptionV3 allows the model to inherit this ability to discern intricate patterns at various scales. The pre-trained weights enable the network to understand complex hierarchical structures present in medical images, contributing to improved feature extraction and enhancing the model's capability to detect subtle abnormalities indicative of cancer.

3.2.3 Resnet50

ResNet50 allows deep network training without vanishing gradient concerns by bypassing one or more layers using residual connections. Residual Blocks with skip connections and batch normalization help train deep networks. The network learns identity mappings quicker with residual connections. Using ResNet50 for transfer learning offers a major benefit in overcoming the difficulties involved in training extremely deep neural networks. The model can efficiently collect and transmit pertinent information across the layers thanks to the addition of residual connections and skip connections. By using pre-trained weights from ResNet50, vanishing gradient issues are mitigated, making training on the histopathologic cancer detection dataset easier and making it easier to extract hierarchical features that are essential for precise diagnosis.

3.2.4 Densenet

DenseNet has dense connection. Each layer feeds into the next. DenseNet has dense blocks where each layer accepts input from previous levels and transmits features to following layers. Dense connection reuses features and minimizes parameters, improving parameter efficiency. With its dense connection patterns, DenseNet121 provides a distinct advantage in parameter efficiency and feature reuse. The model may inherit this efficiency by transfer learning from DenseNet121, which enhances its generalization skills on the histopathologic dataset. Dense connections guarantee that all previous layers' information reaches each layer, promoting a more comprehensive comprehension of the image's characteristics. The extraction of pertinent patterns linked to both benign and malignant tissues is aided by this shared knowledge.

3.2.5 Custom CNN

The term custom CNN refers to a network that has been developed expressly for the purpose at hand. Either it will be completely original or it will contain architectural aspects that are influenced by models that already exist. Custom CNN enable the architecture to be customized according to the particular features of the dataset and the intricacies of the issue. When it comes to experimenting with different layer types, sizes, and connection patterns, its design offers a great deal of versatility. There are several reasons for applying CNN in addition to transfer learning. In comparison to transfer learning, a custom Convolutional Neural Network (CNN) presents distinct advantages in the context of histopathologic cancer detection. One primary advantage lies in the tailored architecture that allows for the specific customization of network layers to align with the unique characteristics of histopathologic images. This customization enables the incorporation of domain-specific knowledge, facilitating the design of layers and connections that effectively capture relevant patterns for the targeted task. Custom CNNs may highlight domain-specific characteristics pertinent to histopathologic pictures, unlike pre-trained models. This flexibility lets make model fine-tune the design based on a thorough knowledge of the dataset to identify cancer detection trends. A custom CNN allows to tune learning rates, dropout rates, and layer sizes to optimize job performance.

3.3 Advanced Data Augmentation

Addressing the challenges posed by limited annotated data, we employed advanced data augmentation strategies. Rotation, shift, shear, and zoom operations were carefully designed to augment the dataset, thereby boosting the generalization capabilities of each model.

3.4 Comprehensive Performance Analysis

The research work conducted an in-depth analysis of each model's performance metrics. Accuracy and loss were thoroughly evaluated, providing valuable insights into the strengths of each architecture in capturing intricate histological patterns indicative of cancer.

3.5 Results and Significance

The results showcased the effectiveness of each individual CNN architecture, with superior performance metrics validating their efficacy in histopathologic cancer detection. The experimentation is carried out in Google Colab. The findings underscored the importance of selecting appropriate architectures tailored to specific tasks, paving the way for advancements in automated histopathologic analysis. This research held potential applications in early cancer diagnosis and treatment planning, contributing to the ongoing evolution of medical image analysis.

4. RESULTS AND DISCUSSION

4.1 Applying CNN

The Keras framework is used to carefully design the histopathologic cancer detection CNN architecture. Firstly, normalization is applied to the pixel values of the images by dividing each value by 255.0. This step standardizes the pixel intensities, ensuring a consistent numerical range between 0 and 1. Subsequently, reshaping of the data array is performed. This adjustment is crucial to align the data structure with the expected format for the subsequent convolutional neural network (CNN) model. The reshaped dimensions encompass the number of samples, image size, and the number of color channels (RGB). Additionally, the target array, representing the labels or categories for each image, undergoes a conversion into a NumPy array. This conversion is essential for establishing a coherent and compatible format for the subsequent training process. Later, data is divided as train and test sets. The total number of images in the dataset are 91,913. The number of images in train set are 82,721 and number of images in test set are 9,121.

CNN extracts hierarchical characteristics needed for histopathologic picture categorization using consecutive layers. The first layer, implicitly specified by input data form, prepares for feature extraction. The first convolutional layer extracts fundamental information from histopathologic pictures using 150 3x3 kernel filters. Non-linearity from the Rectified Linear Unit (ReLU) activation function helps the model capture complicated patterns. A max-pooling layer with a 2x2 window downsamples spatial dimensions to preserve important information.

After a second convolutional layer with 80 filters, a max-pooling layer extracts features. An additional third convolutional layer with 50 filters enhances the extraction of higher-level characteristics needed to distinguish benign and malignant tissues. Each convolutional layer has ReLU activation for non-linear feature transformations. The epoch wise accuracy and loss

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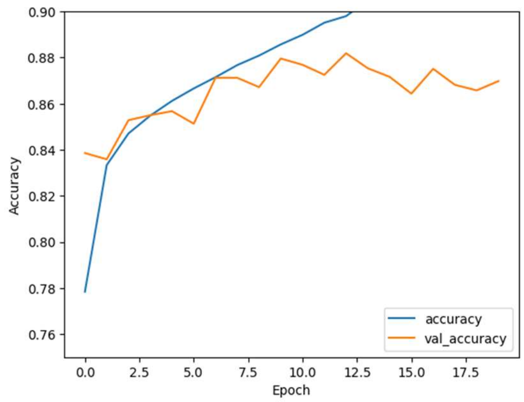
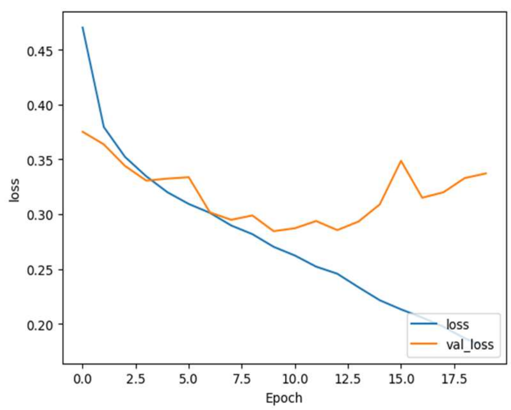
for custom CNN is shown in Figure 2. The accuracy acquired with custom CNN is 88%.



(a) Epoch wise Accuracy for Custom CNN

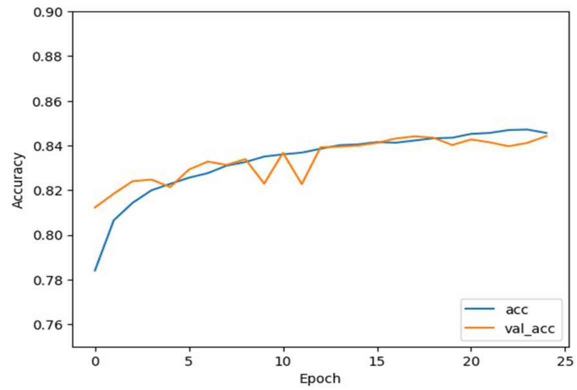


(b) Epoch wise Loss for Custom CNN

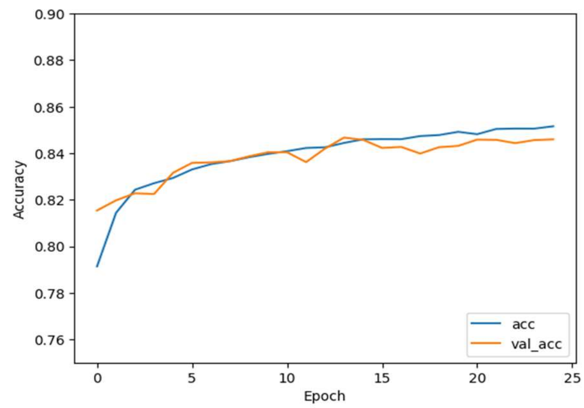
Figure 2: Accuracy and Loss for Custom CNN

4.2. *Applying VGG16 & VGG19*

To implement the VGG16 & VGG19 models for histopathologic cancer detection, the first step involves importing the VGG16, VGG19 architectures from a chosen deep learning library, such as TensorFlow or PyTorch. Subsequently, the fully connected layers from the original VGG16, VGG19 architecture are removed, retaining only the convolutional base. This modification aims to adapt the model to the specific characteristics of histopathologic images. Optionally, custom fully connected layers may be added to the network, offering flexibility to tailor the architecture to the unique requirements of the histopathologic cancer detection task, thereby enhancing its ability to extract relevant features and make accurate predictions. Training occurred on existing data splits, spanning 25 epochs with a batch size of 16. The image size used for VGG16 and VGG19 are 75 by 75. The accuracy achived with VGG16 and VGG19 model is 84.6%, 84.4% respectively. The epoch wise accuracies of VGG16 and VGG19 are shown in Figure 3.



(a) Epoch wise Accuracy for VGG16



(b) Epoch wise Accuracy for VGG19

Figure 3: Accuracy for VGG16 and VGG19

4.3. *Applying InceptionV3*

The InceptionV3 model is loaded with a modified input size of (75, 75, 3), aligning with the characteristics of the histopathologic images under consideration. To tailor the model for the specific cancer detection task, the layers of the InceptionV3 model are frozen, preventing further weight updates during training. Following this, a GVP layer is applied to decrease spatial dimensions, allowing the model to focus on essential features. A fully connected layer with 256 hidden units and ReLU activation is added to capture high-level abstractions from the global features. To prevent overfitting, a dropout layer with a rate of 0.5 is introduced. Finally, a sigmoid layer with a single node is appended to generate binary classification predictions. The compiled model utilizes the RMSprop optimizer and employs binary crossentropy as the loss function. The model is trained on a dataset divided into training and validation sets using a batch size of 32 over 25 epochs. The accuracy achieved with InceptionV3 is

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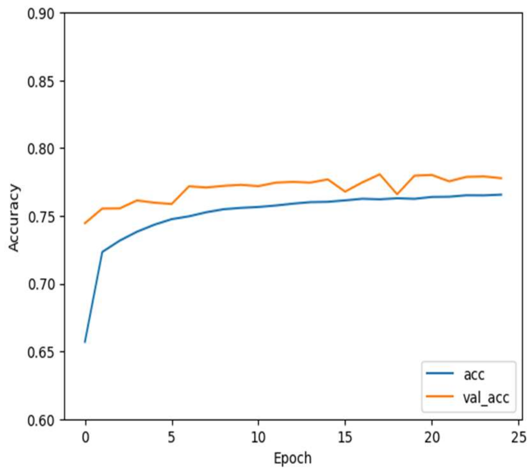
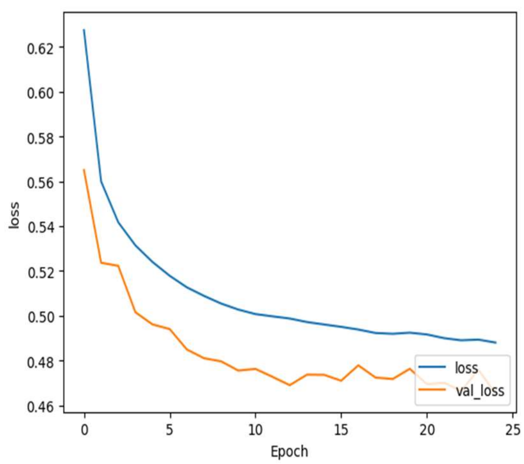
82.5%. The epoch wise accuracy, loss of Inception V3 are shown in Figure 4.



(a) Epoch wise accuracy for Inception V3



(b) Epoch wise loss for Inception V3

Figure.4:Epoch-wise Accuracy & Loss for InceptionV3

4.4. Applying Resnet50

The proposed Resnet50 model utilized pre-trained weights from the ImageNet dataset, and its layers were frozen to retain learned features. A Global Average Pooling layer was added after the convolutional base to capture spatial information efficiently. Further customization included the introduction of a fully connected layer and 256 hidden units and ReLU activation for enhanced feature extraction. To address overfitting, a dropout layer with a rate of 0.5 was incorporated. The final layer employed a sigmoid activation function with a single node, enabling binary classification for cancer detection. The optimizer used in the modes is “adam”, utilizing binary cross-entropy as the loss function. Training occurred on existing data splits, spanning 25 epochs with a batch size of 16. The image size used for VGG16 and VGG19 are 75 by 75. The accuracy achieved with resnet50 is 78%.

4.5. Applying Densenet121

DenseNet121, with weights initialized from ImageNet, is utilized as the base model for feature extraction. The convolutional layers of DenseNet121 are frozen to preserve pre-trained weights. A custom model is constructed by adding global average pooling, a dense layer with 128 units and ReLU activation, dropout regularization for generalization, and a final dense layer with a sigmoid activation for binary classification. The accuracy achieved with Densenet121 is 85.6%.

4.6 Comparison of applied models

The comparison of proposed models is shown in Table 1 and Figure 5. The CNN model has given highest accuracy of 88%. Next, Densenet121 has given good accuracy of 85.6%. After that, VGG16 and VGG19 given accuracy of 84.6% and 84.4% respectively. Later, InceptionV3, has given an accuracy of 82.5% and, Resent50 an accuracy of 78%. Among all the applied models, custom CNN has given good accuracy, hence the best model for cancer detection is custom CNN.

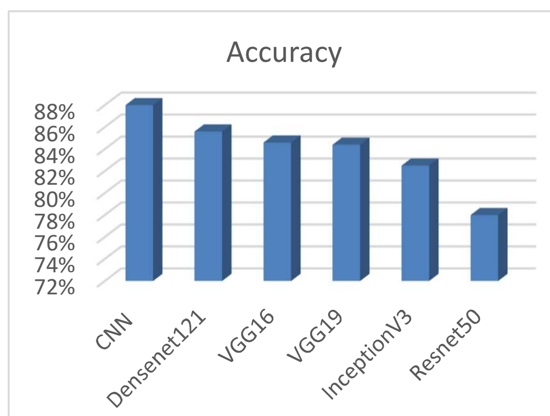


Figure 5. Comparison of proposed models

Table 1. Comparsion of applied models

Model	Accuracy
CNN	88%
Densenet121	85.6%
VGG16	84.6%
VGG19	84.4%
InceptionV3	82.5%
Resnet50	78%

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The major findings of this research highlight the superior performance of the Custom CNN model with good accuracy by outperforming other CNN architectures and existing methods. Advanced data augmentation techniques significantly enhanced model generalization, addressing limitations in annotated data and improving overall accuracy in histopathologic cancer detection.

4.7. Comparison with Existing Work

Table 2 and figure 6 shows comparison of proposed method with existing approaches.The Variational Autoencoder achieved a modest accuracy of 73%, suggesting room for improvement in effectively discerning cancerous and non-cancerous tissue samples. Conversely, the Transfer Learning approach boasted a higher accuracy of 86%, capitalizing on pre-trained models to adapt features for enhanced performance. A Hybrid Approach, amalgamating diverse techniques, demonstrated an accuracy of 84.85%, highlighting the potential advantages of integrating multiple methodologies. However, surpassing all others, the Proposed Customized CNN excelled with an accuracy of 88%.

Table 2. Comparsion with existing models

Model	Accuracy
Variational Autoencoder [6]	73%
Transfer Learning [16]	86%
Hybrid Approach [18]	84.85%
Proposed Customized CNN	88%

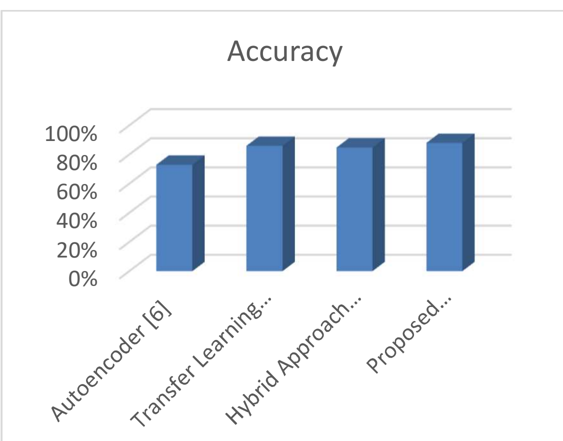

Figure 6. Comparison with existing models

5. CONCLUSION

This research delved into the critical realm of histopathologic cancer detection, a pivotal aspect in the early stages of diagnosis and treatment planning. Leveraging a diverse set of Convolutional Neural Network (CNN) architectures, including VGG19, InceptionV3, ResNet50, DenseNet121, and a custom CNN, the study is aimed to enhance the efficacy of histopathologic cancer detection. The criteria for assessing the effectiveness of each CNN model were based on performance metrics such as accuracy, precision, recall, and F1-score. The investigation employed transfer learning from both general image datasets like ImageNet and specialized medical imaging datasets, tailoring the models to capture unique histopathologic characteristics. Through a meticulous examination of each CNN architecture independently, the research unraveled their distinct contributions to feature extraction, shedding light on their individual strengths. The experiments utilized a Cancer Detection dataset sourced from Kaggle as the foundation, creating a robust framework for comprehensive evaluations. Advanced data augmentation techniques, including rotation, shift, shear, and zoom, were strategically implemented to address the challenges posed by limited annotated data. These techniques were crucial in enhancing the generalization capabilities of each model and improving performance metrics. The obtained results underscore the effectiveness of each individual CNN architecture, with superior performance metrics demonstrated across the board. The custom CNN model exhibited the highest accuracy of 88%, followed by DenseNet121 with 85.6%, VGG16 with 84.6%, VGG19 with 84.4%, InceptionV3 with 82.5%, and ResNet50 with 78%. These performance results were analyzed to determine the relative effectiveness of each architecture, confirming that CNN models significantly contribute to advancing histopathologic cancer detection. These findings affirm the potential of CNN architectures in advancing histopathologic cancer detection, paving the way for improved diagnostic accuracy and patient care in oncology.

REFERENCES

[1] N. Manjunathan, N. Gomathi and S. Muthulingam, "Early Detection of Breast Cancer using Machine Learning," *2023 International Conference on Sustainable Computing and Smart Systems (ICSCSS)*, Coimbatore, India, 2023, pp. 165-169, doi:

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

10.1109/ICSCSS57650.2023.10169777.

[2] M. Nasser and U. K. Yusof, "Deep Learning Based Methods for Breast Cancer Diagnosis: A Systematic Review and Future Direction," *Diagnostics,* vol. 13, no. 1. MDPI AG, p. 161, Jan. 03, 2023. doi: 10.3390/diagnostics13010161.

[3] M. Naqvi, S. Q. Gilani, T. Syed, O. Marques, and H.-C. Kim, "Skin Cancer Detection Using Deep Learning—A Review," *Diagnostics*, vol. 13, no. 11. MDPI AG, p. 1911, May 30, 2023. doi: 10.3390/diagnostics13111911..

[4] T. A. Toma et al., "Breast Cancer Detection Based on Simplified Deep Learning Technique With Histopathological Image Using BreaKHis Database," *Radio Science*, vol. 58, no. 11. American Geophysical Union (AGU), Nov. 2023. doi: 10.1029/2023rs007761.

[5] M. Mokoatle, V. Marivate, D. Mapiye, R. Bornman, and Vanessa. M. Hayes, "A review and comparative study of cancer detection using machine learning: SBERT and SimCSE application," *BMC Bioinformatics*, vol. 24, no. 1. Springer Science and Business Media LLC, Mar. 23, 2023. doi: 10.1186/s12859-023-05235-x.

[6] H. V. Guleria et al., "Enhancing the Breast Histopathology Image Analysis for Cancer Detection Using Variational Autoencoder," International Journal of Environmental Research and Public Health, vol. 20, no. 5. MDPI AG, p. 4244, Feb. 27, 2023. doi: 10.3390/ijerph20054244.

[7] M. Junaid Umer, M. Sharif, M. Alhaisoni, U. Tariq, Y. Jin Kim, and B. Chang, "A Framework of Deep Learning and Selection-Based Breast Cancer Detection from Histopathology Images," Computer Systems Science and Engineering, vol. 45, no. 2. Computers, Materials and Continua (Tech Science Press), pp. 1001–1016, 2023. doi: 10.32604/csse.2023.030463.

[8] D. Hrizi, K. Tbarki, M. Attia and S. Elasmi, "Lung cancer detection and nodule type classification using image processing and machine learning," 2023 International Wireless Communications and Mobile Computing (IWCMC), Marrakesh, Morocco, 2023, pp. 1154-1159, doi: 10.1109/IWCMC58020.2023.10183237.

[9] N. K. Mudaliar, S. Redekar, N. M. Kadam and J. Ramachandran, "Machine Learning-based Prediction Model for Cancer Detection," 2023 2nd International Conference on Applied Artificial Intelligence and Computing (ICAAIC), Salem, India, 2023, pp. 383-388, doi: 10.1109/ICAAIC56838.2023.10140323.

[10] S. G and R. G, "A Novel and Robust Breast Cancer classification based on Histopathological Images using Naive Bayes Classifier," 2023 International Conference on Artificial Intelligence and Knowledge Discovery in Concurrent Engineering (ICECONF), Chennai, India, 2023, pp. 1-8, doi: 10.1109/ICECONF57129.2023.10083855.

[11] N. Kapoor, A. Gupta and K. Meenakshi, "EfCNN-Net: Smart Detection of Colon and Lung Cancer using Histopathological Images," 2023 3rd International Conference on Intelligent Technologies (CONIT), Hubli, India, 2023, pp. 1-6, doi: 10.1109/CONIT59222.2023.10205918.

[12] A. S. Sakr, "Automatic Detection of Various Types of Lung Cancer Based on Histopathological Images Using a Lightweight End-to-End CNN Approach," 2022 20th International Conference on Language Engineering (ESOLEC), Cairo, Egypt, 2022, pp. 141-146, doi: 10.1109/ESOLEC54569.2022.10009108.

[13] R. D. Mohalder, F. Bin Ali, L. Paul and K. Hasan Talukder, "Deep Learning-Based Colon Cancer Tumor Prediction Using Histopathological Images," 2022 25th International Conference on Computer and Information Technology (ICCIT), Cox's Bazar, Bangladesh, 2022, pp. 629-634, doi: 10.1109/ICCIT57492.2022.10054766.

[14] F. He et al., "Multi-Instance Classification of Histopathological Breast Cancer Images with Visual Explanation," 2022 16th IEEE International Conference on Signal Processing (ICSP), Beijing, China, 2022, pp. 431-436, doi: 10.1109/ICSP56322.2022.9965331.

[15] D. P. P, J. K. Radhakrishnan, K. S. Aravind, P. R. Nambiar, and N. Sampath, "Detection of Non-small cell Lung Cancer using Histopathological Images by the approach of Deep Learning," 2022 2nd International Conference on Intelligent Technologies (CONIT). IEEE, Jun. 24, 2022. doi: 10.1109/conit55038.2022.9847945.

[16] C. Hava Muntean and M. Chowkkar, "Breast Cancer Detection from Histopathological Images using Deep Learning and Transfer Learning," 2022 7th International Conference on Machine Learning Technologies (ICMLT). ACM, Mar. 11, 2022. doi: 10.1145/3529399.3529426.

[17] A. A. Ahmed, M. Abouzid, and E. Kaczmarek, "Deep Learning Approaches in Histopathology," Cancers, vol. 14, no. 21.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

MDPI AG, p. 5264, Oct. 26, 2022. doi: 10.3390/cancers14215264.

[18] G. Sahoo, A. Kumar Nayak, P. Kumar Tripathy, and J. Tripathy, "A novel machine learning based hybrid approach for breast cancer relapse prediction," Indonesian Journal of Electrical Engineering and Computer Science, vol. 32, no. 3. Institute of Advanced Engineering and Science, p. 1655, Dec. 01, 2023. doi: 10.11591/ijeecs.v32.i3.pp1655-1663.

[19] V. S. Sowmya Reddy, Chandan K, Nimmy P, T.V. Smitha, K. V. Nagaraja, "OLGV3 NET: Optimized Lightgbm with Inceptionv3 for Accurate Multi-Class Breast Cancer Image Classification Journal of Theoretical and Applied Information Technology ,December 2023. Vol.101. No 24.

[20] Q. B. Baker and A. Abu Qutaish, "Evaluation of Histopathological Images Segmentation Techniques for Breast Cancer Detection," 2021 12th International Conference on Information and Communication Systems (ICICS), Valencia, Spain, 2021, pp. 134-139, doi: 10.1109/ICICS52457.2021.9464594.

[21] J. Xie, R. Liu, J. Luttrell IV, and C. Zhang, "Deep Learning Based Analysis of Histopathological Images of Breast Cancer," Frontiers in Genetics, vol. 10. Frontiers Media SA, Feb. 19, 2019. doi: 10.3389/fgene.2019.00080.

[22] C. Kaushal, D. Koundal and A. Singla, "Comparative Analysis of Segmentation Techniques using Histopathological Images of Breast Cancer," 2019 3rd International Conference on Computing Methodologies and Communication (ICCMC), Erode, India, 2019, pp. 261-266, doi: 10.1109/ICCMC.2019.8819659.

[23] A. K. Arslan, Ş. Yaşar and C. Çolak, "Breast cancer classification using a constructed convolutional neural network on the basis of the histopathological images by an interactive web-based interface," 2019 3rd International Symposium on Multidisciplinary Studies and Innovative Technologies (ISMSIT), Ankara, Turkey, 2019, pp. 1-5, doi: 10.1109/ISMSIT.2019.8932942.

[24] M. Jannesari et al., "Breast Cancer Histopathological Image Classification: A Deep Learning Approach," 2018 IEEE International Conference on Bioinformatics and Biomedicine (BIBM), Madrid, Spain, 2018, pp. 2405-2412, doi: 10.1109/BIBM.2018.8621307.

[25] M. Ezzulddin Merza, S. H. Hussein, and Q. I. Ali, "Identification scheme of false data injection attack based on deep learning algorithms for smart grids," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 30, no. 1. Institute of Advanced Engineering and Science, p. 219, Apr. 01, 2023. doi: 10.11591/ijeecs.v30.i1.pp219-228.

[26] https://www.kaggle.com/competitions/histopathologic-cancer-detection/data