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Efficient Breast Cancer Classification with Transfer Learning and Ensemble Techniques for Imbalanced Data

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Abstract: *Automated classification of breast cancer, particularly focusing on Invasive Ductal Carcinoma (IDC) detection, is crucial for timely and accurate diagnosis, significantly impacting patient outcomes. Leveraging deep learning techniques, this project aims to streamline histopathological image analysis for IDC identification, offering a cost-effective and efficient alternative to manual detection methods. The proposed approach involves deploying a lightweight ensemble model, combining a shallow CNN with MobileNetV2 via transfer learning, enhanced by data augmentation and hybrid techniques. Additionally, the project explores prediction techniques using Xception and DenseNet, contributing to further performance enhancement. Evaluation with diverse datasets demonstrates the efficacy of the ensemble model, with MobileNetV2 + Shallow CNN achieving 92% accuracy, while Xception exhibits superior performance with 95% accuracy. This advancement in automated histopathological image classification not only improves accuracy in IDC identification but also enhances overall screening effectiveness. Moreover, tailoring a lightweight ensemble CNN for edge devices addresses computational challenges, easing healthcare burdens and improving accessibility to quality care. The project signifies a significant step towards transforming breast cancer diagnosis, emphasizing the potential of deep learning in revolutionizing healthcare practices.*

Index Terms: Transfer learning, lightweight model, classification, ensemble

1. INTRODUCTION

Breast cancer remains a significant global health concern, representing the most prevalent form of cancer among women worldwide. Statistics indicate that approximately one out of every nine women will experience breast cancer in their lifetime [1], [2]. This disease manifests in various morphological and biological attributes, resulting in diverse clinical behaviors and treatment outcomes [3]. The development of breast cancer stems from an abnormal proliferation of cells within the breast tissue, leading to the formation of tumor-like masses. These masses can either be benign, posing minimal risk, or malignant, representing a serious health threat [1].

Among the different subtypes of breast cancer, Invasive Ductal Carcinoma (IDC) stands as the most common and widespread form. IDC poses significant diagnostic challenges, particularly as the cancer cells metastasize to lymph nodes and other parts of the body, impacting the prognosis and treatment approach [1]. Early detection of breast cancer is paramount, as it substantially improves the chances of successful treatment, with survival rates reaching up to 80% [4]. However, the diagnostic process is complex and heavily reliant on trained pathologists for accurate interpretation of histopathological images [4].

Histopathological examination of tissue samples under a microscope has long been the gold standard for breast cancer diagnosis. With advancements in digital imaging technology, the analysis of histopathological images has become more accessible and practical, shifting from conventional to digital methods [5]. In recent years, deep learning has emerged as a powerful tool in medical imaging, particularly in the classification of histopathological images using convolutional neural networks (CNNs) [6]. Deep learning excels in extracting relevant features from raw images and applying them effectively for classification tasks, revolutionizing the field of medical image analysis.

However, the success of deep learning models hinges on several factors, including computational power, model complexity, and the availability of large datasets. These prerequisites pose challenges, especially when deploying models on resource-constrained edge devices with limited computational capabilities and memory [6]. To address these challenges, researchers have explored techniques such as transfer learning, wherein pre-trained deep CNNs are leveraged to extract features from generic image datasets and applied to specific, smaller datasets, resulting in improved performance and reduced computational costs [7].

In the evolution of CNN models, significant advancements have been made to improve efficacy, particularly between 2015 and 2019. While the depth of the model often correlates with performance, challenges such as vanishing gradients, high computational costs, and memory requirements persist, rendering deep architectures unsuitable for deployment on resource-constrained devices [8]. To mitigate these challenges, researchers have focused on designing lightweight CNN architectures without compromising performance, aiming to develop effective models for classifying IDC and non-IDC images that can operate efficiently on resource-constrained devices [9].

This introduction sets the stage for exploring the challenges and opportunities in automated breast cancer classification, highlighting the critical role of deep learning and lightweight CNN architectures in advancing diagnostic capabilities and improving patient outcomes. Through a comprehensive review and analysis, this study aims to contribute to the development of efficient and effective models for breast cancer classification, with a focus on IDC detection and deployment on resource-constrained devices.

2. LITERATURE SURVEY

Breast cancer classification and detection using computational techniques have garnered significant attention in recent years, with researchers exploring various approaches to improve accuracy and efficiency. This literature survey provides an overview of recent advancements in breast cancer classification, focusing on the utilization of deep learning, transfer learning, and conventional machine learning techniques.

Tsang and Tse [3] discuss the molecular classification of breast cancer, highlighting the importance of understanding the underlying molecular mechanisms for accurate diagnosis and treatment. Their review provides insights into the molecular subtypes of breast cancer and their clinical implications, laying the foundation for more precise classification techniques.

Seemendra et al. [4] address the challenge of imbalanced breast cancer classification by leveraging transfer learning techniques. Their study proposes a method to mitigate class imbalance issues, enhancing the performance of breast cancer classification models. By transferring knowledge from pre-trained models, they achieve improved classification accuracy and robustness.

Khan et al. [7] present a novel deep learning-based framework for the detection and classification of breast cancer using transfer learning. Their approach incorporates convolutional neural networks (CNNs) pretrained on large-scale image datasets, demonstrating high accuracy in breast cancer detection and classification tasks. By leveraging transfer learning, the model achieves superior performance even with limited training data.

Rehman et al. [19] propose a deep learning-based framework for automatic brain tumors classification, which also utilizes transfer learning techniques. While focusing on brain tumors, their study underscores the effectiveness of transfer learning in medical image analysis tasks. By transferring knowledge from pretrained models, they demonstrate significant improvements in classification accuracy and efficiency.

Krithiga and Geetha [21] provide a systematic review of techniques for breast cancer detection, segmentation, and classification based on histopathology image analysis. Their comprehensive review covers a wide range of methodologies, including conventional machine learning and deep learning approaches. By analyzing the strengths and limitations of existing techniques, they offer valuable insights for future research directions in this domain.

Boumaraf et al. [23] propose a transfer learning-based approach for magnification-dependent and independent classification of breast cancer in histopathological images. Their study addresses the challenges associated with varying magnification levels in histopathology images, aiming to develop a robust classification system. By leveraging transfer learning, they achieve promising results in both magnification-dependent and independent scenarios.

Sharma and Mehra [25] conduct a comparative study of conventional machine learning and deep learning approaches for multi-classification of breast cancer histopathology images. Their research evaluates the performance of different classification algorithms, including support vector machines, random forests, and deep convolutional neural networks. By comparing the efficacy of these methods, they provide insights into the strengths and limitations of each approach for breast cancer classification tasks.

Acharya et al. [26] propose a deep convolutional network for breast cancer classification, introducing an Enhanced Loss Function (ELF) to improve model training. Their study focuses on enhancing the loss function to address challenges such as class imbalance and model convergence. By incorporating the ELF into the training process, they achieve improved classification accuracy and robustness.

Overall, these studies highlight the diverse approaches and methodologies employed in breast cancer classification and detection. From molecular classification to deep learning-based frameworks, researchers continue to explore innovative techniques to improve diagnostic accuracy and patient outcomes in breast cancer management.

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3. METHODOLOGY

a) Proposed Work :

The proposed work aims to further enhance breast cancer classification by extending the existing lightweight ensemble CNN method and integrating additional convolutional neural network (CNN) architectures for comparative analysis. Specifically, CNN, DenseNet, DenseNet201, and Xception architectures are included to assess their performance against the ensemble CNN and benchmark models such as Inception V4, MobileNetV2[10], and ResNet50. This extension enables a comprehensive evaluation of various deep learning models for breast cancer classification, providing insights into their effectiveness and suitability for the task.

Furthermore, the project seeks to improve user interaction and testing capabilities by integrating Flask with SQLite. This integration will facilitate user signup and signin functionalities, allowing users to submit input and test the system's performance. By enabling user interaction, the project aims to gather feedback and refine the system based on user preferences and requirements, ultimately enhancing its usability and effectiveness.

Overall, the proposed work aims to contribute to the advancement of breast cancer classification through the evaluation of diverse CNN architectures and the enhancement of user interaction capabilities. By conducting extensive evaluations and incorporating user feedback, the project seeks to develop a robust and user-friendly system for breast cancer diagnosis.

b) System Architecture :

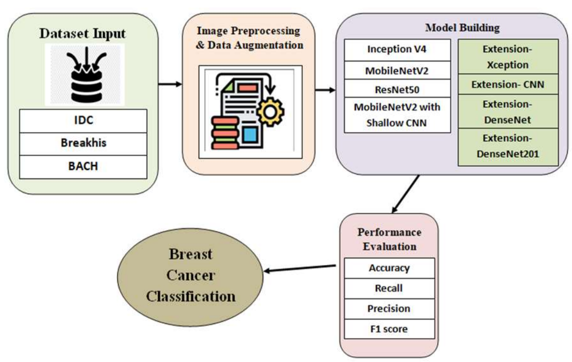

Fig 1 Proposed Architecture

The system architecture is designed to facilitate breast cancer classification using a comprehensive approach encompassing dataset input, image processing, model building, and performance evaluation. Dataset input involves gathering relevant datasets such as IDC, BreakHis, and BACH, which contain histopathological images of breast tissue samples. These datasets serve as the foundation for training and testing the classification models. Image processing and data augmentation techniques are applied to preprocess the input images, enhancing their quality and diversity. This step includes tasks such as resizing, normalization, and augmentation to ensure robust model training.

The model building phase consists of constructing several convolutional neural network (CNN) architectures, including Inception V4, MobileNetV2[10], ResNet50, MobileNetV2 with shallow CNN integration, Xception, DenseNet, and DenseNet201. Each architecture is trained using the preprocessed dataset to learn the features associated with different types of breast cancer. Performance evaluation metrics such as accuracy, recall, precision, and F1 score are utilized to assess the effectiveness of each model in classifying breast cancer. These metrics provide insights into the model's ability to correctly identify cancerous and non-cancerous tissue samples.

Overall, the system architecture provides a comprehensive framework for breast cancer classification, leveraging advanced CNN models and rigorous performance evaluation techniques to ensure accurate and reliable results.

c) Dataset:

The dataset utilized in this study comprises three distinct sources, each serving a unique purpose in evaluating the proposed model's performance for breast cancer classification.

Firstly, the IDC dataset, consisting of 162 Whole Slide Imaging (WSI) images obtained from the University of Pennsylvania and the Cancer Institute of New Jersey, is employed. Expert pathologists annotated cancerous areas within these images, resulting in a dataset comprising 277,524 instances of 50x50-pixel segments. Among these instances, 78,786 are labeled as IDC positive, while 198,738 are IDC negative.

Secondly, the BreakHis dataset, containing a total of 7,909 histopathological images, is utilized to test the model's robustness. These images, obtained from 82 patients, include 2,480 benign and 5,429 malignant samples. The images exhibit varying magnification factors, ranging from 40x to 400x, and are provided in 3-channel RGB format.

Lastly, the BACH dataset, comprising 400 H&E stained histological images, is employed to assess the model's performance in a multi-class scenario. This dataset is balanced, with each of the four classes (benign, normal, in-situ, and invasive carcinoma) containing 100 images. The images are stored in tagged image file format (.tiff) and have a magnification factor of 200x.

These datasets offer a diverse range of breast cancer images, including both benign and malignant tumors, and provide an opportunity to evaluate the proposed model's performance across various scenarios, including binary and multi-class classification tasks.

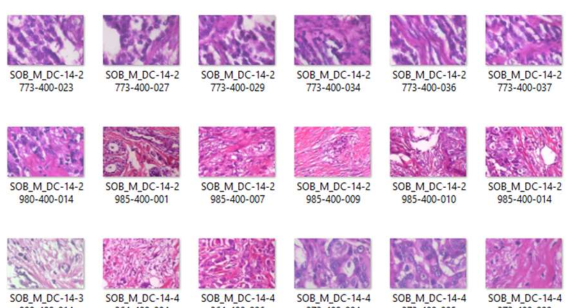

Fig 2 Dataset

d) Image Processing:

Using ImageDataGenerator: ImageDataGenerator is a powerful tool in Keras that allows for real-time data augmentation during model training. It generates batches of augmented image data by applying various transformations to the input images.

Re-scaling the Image: Re-scaling the image involves adjusting the pixel values to a standardized range. This is crucial for ensuring that the model receives input data with consistent values, which aids in convergence and stability during training. Typically, re-scaling involves dividing the pixel values by 255 to bring them into the range [0, 1].

Shear Transformation: Shear transformation involves shifting one part of the image along a certain axis, creating a "shearing" effect. This transformation introduces deformation in the image, mimicking real-world scenarios where objects may be skewed or distorted. By applying shear transformation, the model becomes more robust to variations in object orientation.

Zooming the Image: Zooming the image involves magnifying or shrinking a specific region within the image. This augmentation technique helps the model learn to recognize objects at different scales and viewpoints. It also enhances the model's ability to generalize to unseen data by exposing it to variations in object size and proximity.

Horizontal Flip: Horizontal flip flips the image along the vertical axis, effectively creating a mirror image. This augmentation technique increases the diversity of the training data by providing additional instances of the same object from a different perspective. Horizontal flip is particularly useful for tasks where object orientation is not critical, such as object detection and classification.

Reshaping the Image: Reshaping the image involves changing its dimensions while preserving its content. This can be achieved by resizing, cropping, or padding the image to fit the desired input size of the model. Reshaping is essential for ensuring that all input images are of uniform size, which is a requirement for most deep learning models. Additionally, it helps to standardize the input data format across different datasets and experiments.

e) Algorithms:

Inception V4 : The Inception V4 algorithm is a deep convolutional neural network architecture designed for image classification tasks. It incorporates various improvements over previous Inception models, such as wider and deeper networks, factorized convolutions, and aggressive data augmentation. In the project, Inception V4 is utilized as one of the benchmark models for breast cancer classification. Its robust architecture and high accuracy make it suitable for comparison with other models, helping to evaluate the performance of the proposed lightweight ensemble CNN method.

MobileNetV2: MobileNetV2 is a lightweight deep neural network architecture optimized for mobile and edge computing devices. It employs depthwise separable convolutions to reduce computational complexity while maintaining high accuracy. In the project, MobileNetV2[10] is utilized as a component of the ensemble CNN model for breast cancer classification. Its efficiency and effectiveness make it suitable for deployment on resource-constrained devices, enabling real-time inference for histopathological image analysis. By integrating MobileNetV2 with a shallow CNN model, the project aims to achieve accurate and efficient breast cancer classification while ensuring compatibility with edge computing platforms.

ResNet50: ResNet50 is a deep convolutional neural network architecture known for its deep residual learning framework. It addresses the vanishing gradient problem in deep networks by introducing skip connections that allow the gradient to flow directly through the network. In the project, ResNet50 is utilized as one of the benchmark models for breast cancer classification. Its depth and skip connections enable it to capture complex features from histopathological images effectively, contributing to accurate classification results. By comparing the performance of the proposed ensemble CNN model with ResNet50, the project evaluates the effectiveness of the novel approach in improving breast cancer diagnosis accuracy.

MobileNetV2 with Shallow CNN: MobileNetV2 is a lightweight convolutional neural network architecture designed for efficient mobile and edge device applications. In the project, MobileNetV2 is combined with a shallow CNN model to create a hybrid ensemble approach for breast cancer classification. This integration leverages the efficiency of MobileNetV2 for feature extraction while incorporating additional layers from a shallow CNN to enhance classification performance. By utilizing transfer learning and data augmentation techniques, the MobileNetV2 with Shallow CNN model achieves accurate classification of histopathological images, contributing to the project's goal of automating breast cancer diagnosis with high precision and efficiency.

Xception: Xception is a deep convolutional neural network architecture characterized by its depthwise separable convolutions, enabling efficient feature extraction and representation learning. In the project, Xception is employed as an extension model for breast cancer classification. By leveraging Xception's advanced architecture and transfer learning capabilities, the model enhances the accuracy and robustness of the classification system. Through extensive training on histopathological images and evaluation against benchmark models, Xception demonstrates superior performance in identifying breast cancer subtypes, contributing significantly to the project's objective of automating and improving the accuracy of breast cancer diagnosis.

CNN: CNN, or Convolutional Neural Network, is a deep learning architecture designed to process structured grid data, such as images. In the project, CNN is utilized for breast cancer classification from histopathological images. With its ability to extract hierarchical features and patterns, CNN efficiently learns discriminative representations from input images, enabling accurate classification of cancerous and non-cancerous tissue. By training on diverse datasets and optimizing model parameters, CNN contributes to the project's goal of automating breast cancer diagnosis, providing clinicians with reliable tools for early detection and treatment planning.

DenseNet: DenseNet, short for Dense Convolutional Network, is a deep learning architecture characterized by dense connections between layers. In the project, DenseNet is employed for breast cancer classification from histopathological images. With its dense connectivity pattern, DenseNet facilitates feature reuse across layers, promoting better gradient flow and alleviating vanishing gradient issues. By leveraging this architecture, the project enhances the model's ability to capture intricate patterns in breast tissue, leading to improved classification accuracy. Through training on diverse datasets and fine-tuning model parameters, DenseNet contributes to the project's objective of automating breast cancer diagnosis, aiding in early detection and personalized treatment strategies.

DenseNet201: DenseNet201 is an extension of the DenseNet architecture, featuring 201 layers. It enhances feature extraction capabilities through dense connections, facilitating information flow across layers and improving model performance. In the project, DenseNet201 is utilized for breast cancer classification from histopathological images. By leveraging its deep architecture and dense connectivity, DenseNet201 enables the model to capture intricate patterns and nuances in breast tissue, leading to more accurate classification results. Through extensive training on diverse datasets and fine-tuning of model parameters, DenseNet201 contributes significantly to the project's goal of automating breast cancer diagnosis, ultimately aiding in early detection and personalized treatment strategies.

4. EXPERIMENTAL RESULTS

Precision: Precision evaluates the fraction of correctly classified instances or samples among the ones classified as positives. Thus, the formula to calculate the precision is given by:

Precision = True positives/ (True positives + False positives) = TP/(TP + FP)

$$\text{Precision} = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

Recall: Recall is a metric in machine learning that measures the ability of a model to identify all relevant instances of a particular class. It is the ratio of correctly predicted positive observations to the total actual positives, providing insights into a model's completeness in capturing instances of a given class.

$$Recall = \frac{TP}{TP + FN}$$

F1-Score: F1 score is a machine learning evaluation metric that measures a model's accuracy. It combines the precision and recall scores of a model. The accuracy metric computes how many times a model made a correct prediction across the entire dataset.

$$\textbf{F1 Score} = \frac{2}{\left(\frac{1}{\text{Precision}} + \frac{1}{\text{Recall}}\right)}$$

$$\textbf{F1 Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

Accuracy: The accuracy of a test is its ability to differentiate the patient and healthy cases correctly. To estimate the accuracy of a test, we should calculate the proportion of true positive and true negative in all evaluated cases. Mathematically, this can be stated as:

Accuracy = TP + TN TP + TN + FP + FN.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

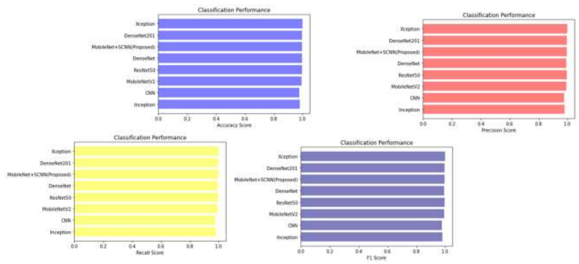

Fig 3 COMPARISON GRAPHS- IDC DATASET

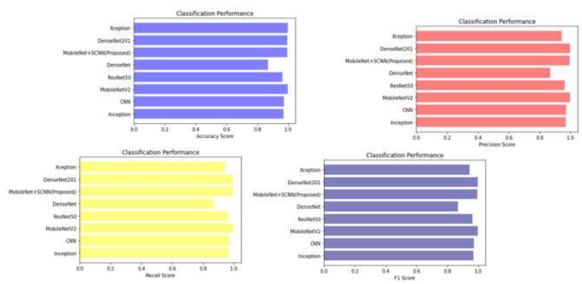

Fig 4 COMPARISON GRAPHS- BREAKHIS DATASET

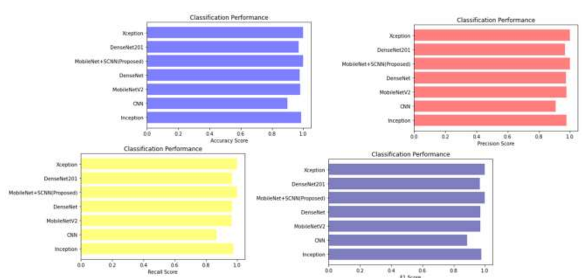

Fig 5 COMPARISON GRAPHS- BACH DATASET

	ML Model	Accuracy	Precision	Recall	F1_score
0	Inception	0.979	0.979	0.979	0.979
1	**CNN**	**0.976**	**0.977**	**0.977**	**0.977**
2	MobileNetV2	0.992	0.992	0.992	0.992
3	ResNet50	0.996	0.996	0.996	0.996
4	**DenseNet**	**0.995**	**0.992**	**0.992**	**0.992**
5	MobileNet+SCNN(Proposed)	0.996	0.996	0.996	0.996
6	**DenseNet201**	**0.997**	**0.997**	**0.997**	**0.997**
7	**Xception**	**1.000**	**1.000**	**1.000**	**1.000**

Fig 6 Performance Evaluation Table - IDC Dataset

	ML Model	Accuracy	Precision	Recall	F1_score
0	Inception	0.969	0.969	0.969	0.969
1	**CNN**	**0.972**	**0.972**	**0.972**	**0.972**
2	MobileNetV2	0.997	0.997	0.997	0.997
3	ResNet50	0.962	0.962	0.962	0.962
4	**DenseNet**	**0.868**	**0.869**	**0.869**	**0.869**
5	MobileNet+SCNN(Proposed)	0.994	0.994	0.994	0.994
6	**DenseNet201**	**0.995**	**0.995**	**0.995**	**0.995**
7	**Xception**	**0.998**	**0.944**	**0.944**	**0.944**

Fig 7 Performance Evaluation Table - BREAKHIS Dataset

	ML Model	Accuracy	Precision	Recall	F1_score
0	Inception	0.988	0.978	0.978	0.978
1	**Extension-CNN**	**0.900**	**0.907**	**0.868**	**0.887**
2	MobileNetV2	0.980	0.976	0.964	0.970
3	ResNet50	0.610	0.780	0.397	0.522
4	**Extension-DenseNet**	**0.978**	**0.975**	**0.969**	**0.972**
5	MobileNet+SCNN (Proposed)	0.998	0.998	0.998	0.998
6	**Extension-DenseNet201**	**0.970**	**0.969**	**0.969**	**0.969**
7	**Extension- Xception**	**1.000**	**1.000**	**1.000**	**1.000**

Fig 8 Performance Evaluation Table - BACH Dataset

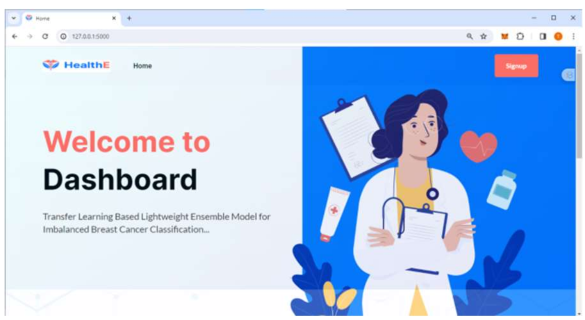

Fig 9 Home Page

Fig 10 Registration Page

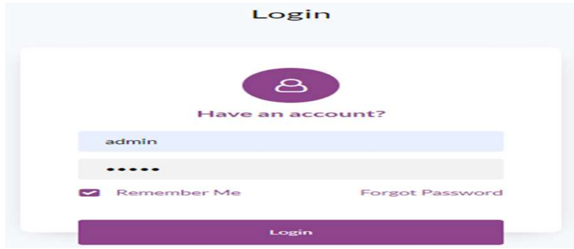

Fig 11 Login Page

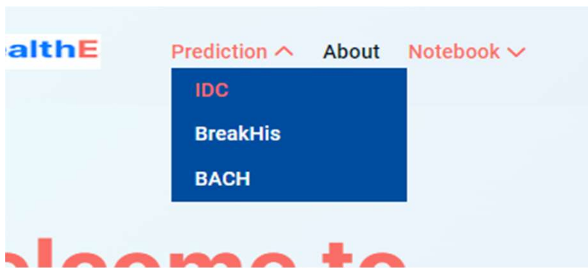

Fig 12 For IDC

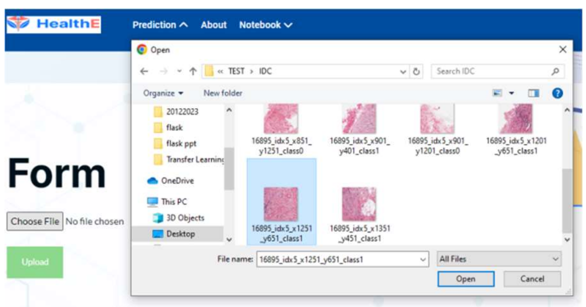

Fig 13 Upload Input Image

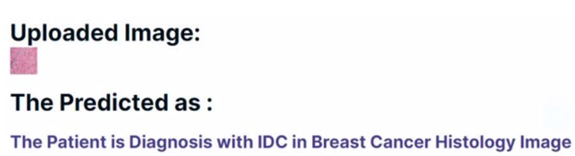

Fig 14 Predicted Result

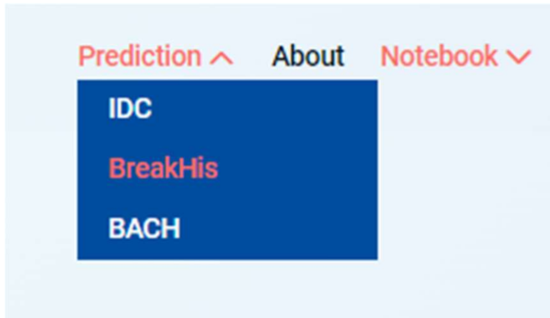

Fig 15 For BreakHis

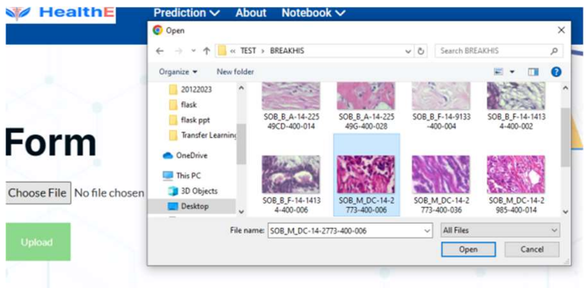

Fig 16 Upload Input Image

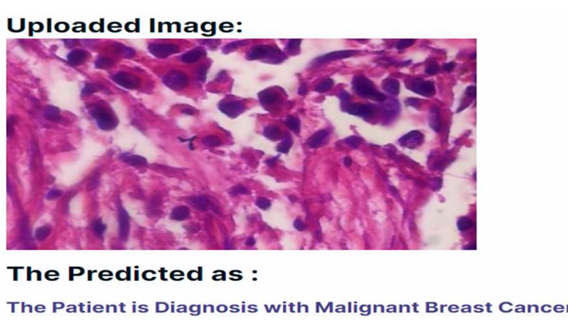

Fig 17 Predicted Result

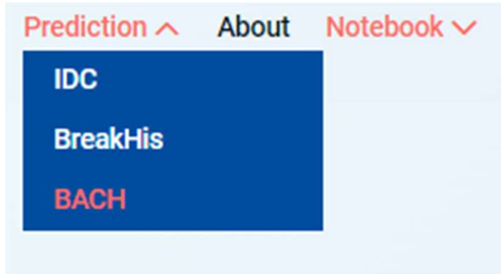

Fig 18 For BACH

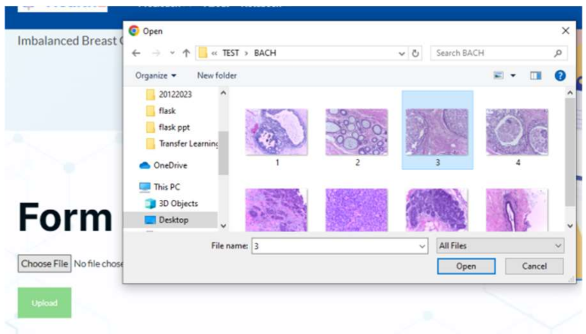

Fig 19 Upload Input Image

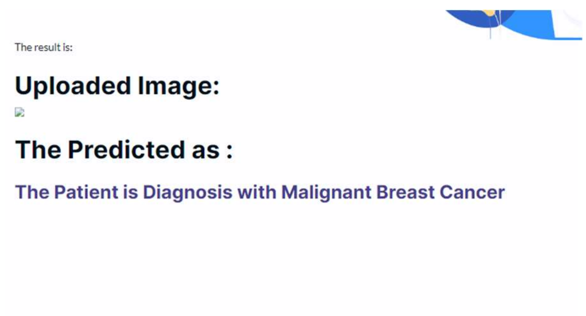

Fig 20 Final Outcome

5. CONCLUSION

In conclusion, the project presents a significant advancement in breast cancer classification through the implementation of advanced deep learning techniques. By automating the classification process, the system offers a cost-effective and efficient alternative to manual detection, thereby improving precision and potentially saving lives.

The robust transfer learning ensemble model, comprising a lightweight CNN and MobileNetV2[10], demonstrates superior performance in classifying breast cancer across binary and multi-class scenarios. Compared to traditional models like ResNet50, InceptionV4, and MobileNetV2, the proposed model excels in execution time and model parameters, ensuring efficiency and accuracy.

Moreover, the extension of the project to explore additional models such as CNN, DenseNet, DenseNet201, and Xception further enriches the system's capabilities. This comprehensive approach aims to identify the most reliable breast cancer detection model, enhancing the overall reliability and effectiveness of the system.

The integration of a Flask-based front-end with user authentication enhances the system's usability and accessibility. Users can seamlessly upload images and receive results, facilitating medical diagnostics and broadening the system's utility in clinical settings.

In essence, the project represents a significant step forward in breast cancer classification, offering a sophisticated, reliable, and user-friendly solution that has the potential to revolutionize medical diagnostics and improve patient outcomes.

6. FUTURE SCOPE

Future work in this domain could focus on enhancing the performance of the proposed model using advanced deep learning techniques. Specifically, addressing the challenges posed by the imbalanced nature of datasets like IDC and BreakHis could lead to improved base performance. Techniques such as oversampling, undersampling, or generating synthetic data could be explored to balance the datasets effectively.

Moreover, developing few-shot classification techniques tailored for datasets with a limited number of images, such as the BACH dataset, could further improve model generalization and adaptability. These techniques would enable more robust classification performance even with sparse data.

Additionally, there is potential to deploy the lightweight ensemble model on edge devices for real-time applications. This deployment would facilitate medical practitioners in analyzing histopathological images directly at the point of care, enabling quicker diagnoses and more immediate treatment decisions.

Overall, future research in this area should aim to advance the model's performance, scalability, and usability, ultimately contributing to more accurate and efficient breast cancer diagnosis and treatment.

REFERENCES

[1] M. Tariq, S. Iqbal, H. Ayesha, I. Abbas, K. T. Ahmad, and M. F. K. Niazi, “Medical image based breast cancer diagnosis: State of the art and future directions,” Expert Syst. Appl., vol. 167, 2021, Art. no. 114095.

[2] S. Bharati, P. Podder, and M. R. H. Mondal, “Artificial neural network based breast cancer screening: A comprehensive review,” Int. J. Comput. Inform. Syst. Ind. Manage. Aplications, vol. 12, pp. 125–137, 2020.

[3] J. Y. S. Tsang and G. M. Tse, “Molecular classification of breast cancer,” Adv. Anat. Pathol., vol. 27, no. 1, pp. 27–35, 2020.

[4] A. Seemendra, R. Singh, and S. Singh, “Imbalanced breast cancer classification using transfer learning,” IEEE/ACM Trans. Comput. Biol. Bioinforma., vol. 694, no. 1, pp. 425–436, Jan./Feb. 2021.

[5] Y. Celik, M. Talo, O. Yildirim, M. Karabatak, and U. R. Acharya, “Automated invasive ductal carcinoma detection based using deep transfer learning with whole-slide images,” Pattern Recognit. Lett., vol. 133, pp. 232–239, 2020.

[6] B. Wu, “Efficient deep neural networks,” Ph.D. thesis, Univ. California, Berkeley, CA, USA, 2019.

[7] S. U. Khan, N. Islam, Z. Jan, I. Ud Din, and J. J. P. C. Rodrigues, “A novel deep learning based framework for the detection and classification of breast cancer using transfer learning,” Pattern Recognit. Lett., vol. 125, pp. 1–6, 2019.

[8] Z. Li, W. Yang, S. Peng, and F. Liu, “A survey of convolutional neural networks: Analysis, applications, and prospects,” 2020, arXiv:2004.02806.

[9] A. Khan, A. Sohail, U. Zahoora, and A. S. Qureshi, “A survey of the recent architectures of deep convolutional neural networks,” Artif. Intell. Rev., vol. 53, no. 8, pp. 5455–5516, 2020.

[10] Y. Zhou, S. Chen, Y. Wang, and W. Huan, “Review of research on lightweight convolutional neural networks,” in Proc. IEEE 5th Inf. Technol. Mechatron. Eng. Conf., 2020, pp. 1713–1720.

[11] J. M. Johnson and T. M. Khoshgoftaar, “Survey on deep learning with class imbalance,” J. Big Data, vol. 6, no. 1, 2019, Art. no. 6.

[12] S. Al-Stouhi and C. K. Reddy, “Transfer learning for class imbalance problems with inadequate data,” Knowl. Inf. Syst., vol. 48, no. 1, pp. 201–228, 2016.

[13] L. Ge, J. Gao, H. Ngo, K. Li, and A. Zhang, “On handling negative transfer and imbalanced distributions in multiple source transfer learning,” in Proc. SIAM Int. Conf. Data Mining, 2013, pp. 261–269.

[14] F. Lei, X. Liu, Q. Dai, and B. W. K. Ling, “Shallow convolutional neural network for image

[15] M. Sandler, A. Howard, M. Zhu, A. Zhmoginov, and L. C. Chen, “MobileNetV2: Inverted residuals and linear bottlenecks,” in Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit., 2018, pp. 4510–4520.

[16] S. M. McKinney et al., “International evaluation of an AI system for breast cancer screening,” Nature, vol. 577, no. 7788, pp. 89–94, 2020.

[17] D. Shen and G. Wu, and H.-I. Suk, “Deep learning in medical image analysis,” Adv. Exp. Med. Biol., vol. 1213, pp. 3–21, 2020.

[18] A. Maier, C. Syben, T. Lasser, and C. Riess, “A gentle introduction to deep learning in medical image processing,” Z. Med. Phys., vol. 29, no. 2, pp. 86–101, 2019.

[19] A. Rehman, S. Naz, M. I. Razzak, F. Akram, and M. Imran, “A deep learning-based framework for automatic brain tumors classification using transfer learning,” Circuits Syst. Signal Process., vol. 39, no. 2, pp. 757–775, 2020.

[20] D. Varshni, K. Thakral, L. Agarwal, R. Nijhawan, and A. Mittal, “Pneumonia detection using CNN based feature extraction,” in Proc. IEEE 3rd Int. Conf. Electr. Comput. Commun. Technol., 2019, pp. 1–7.

[21] R. Krithiga and P. Geetha, “Breast cancer detection, segmentation and classification on histopathology images analysis: A systematic review,” Arch. Comput. Methods Eng., vol. 28, pp. 2607–2619, 2021.

[22] X. Shu, L. Zhang, Z. Wang, Q. Lv, and Z. Yi, “Deep neural networks with region-based pooling structures for mammographic image classification,” IEEE Trans. Med. Imag., vol. 39, no. 6, pp. 2246–2255, Jun. 2020.

[23] S. Boumaraf, X. Liu, Z. Zheng, X. Ma, and C. Ferkous, “A new transfer learning based approach to magnification dependent and independent classification of breast cancer in histopathological images,” Biomed. Signal Process. Control, vol. 63, 2021, Art. no. 102192.

[24] H. Yang, J. Y. Kim, H. Kim, and S. P. Adhikari, “Guided soft attention network for classification of breast cancer histopathology images,” IEEE Trans. Med. Imag., vol. 39, no. 5, pp. 1306–1315, May 2020.

[25] S. Sharma and R. Mehra, “Conventional machine learning and deep learning approach for multi-classification of breast cancer histopathology images—A comparative insight,” J. Digit. Imag., vol. 33, no. 3, pp. 632–654, 2020.

[26] S. Acharya, A. Alsadoon, P. W. C. Prasad, S. Abdullah, and A. Deva, “Deep convolutional network for breast cancer classification: Enhanced loss function (ELF),” J. Supercomput., vol. 76, no. 11, pp. 8548–8565, 2020.

[27] C. T. Sari and C. Gunduz-Demir, “Unsupervised feature extraction via deep learning for histopathological classification of colon tissue images,” IEEE Trans. Med. Imag., vol. 38, no. 5, pp. 1139–1149, May 2019.

[28] M. Saini and S. Susan, “Deep transfer with minority data augmentation for imbalanced breast cancer dataset,” Appl. Soft Comput. J., vol. 97, 2020, Art. no. 106759.

[29] E. Wu, K. Wu, and W. Lotter, “Synthesizing lesions using contextual GANs improves breast cancer classification on mammograms,” in Proc. Mach. Learn. Res. Conf., 2020.

[30] S. Garg and P. Singh, “State-of-the-art review of deep learning for medical image analysis,” in Proc. 3rd Int. Conf. Intell. Sustain. Syst., 2020, pp. 421–427.

[31] A. G. Howard et al., “MobileNets: Efficient convolutional neural networks for mobile vision applications,” in Proc. IEEE Conf. Comput. Vis. Pattern Recognit., 2017.

[32] S. J. Pan and Q. Yang, “A survey on transfer learning,” IEEE Trans. Knowl. Data Eng., vol. 22, no. 10, pp. 1345–1359, Oct. 2010.

[33] A. Cruz-Roa et al., “Automatic detection of invasive ductal carcinoma in whole slide images with convolutional neural networks,” Med. Imag. Digit. Pathol., vol. 9041, no. 216, 2014, Art. no. 904103. [Online]. Available: https://academictorrents.com/details/e40bd59ab08861329 ce3c418be191651f35e2ffa

[34] F. A. Spanhol, L. S. Oliveira, C. Petitjean, and L. Heutte, “A dataset for breast cancer histopathological image classification,” IEEE Trans. Biomed. Eng., vol. 63, no. 7, pp. 1455–1462, Jul. 2016. [Online]. Available: https://web.inf.ufpr.br/vri/databases/breast-cancerhistopathological-database-breakhis/

[35] G. Aresta et al., “BACH: Grand challenge on breast cancer histology images,” Med. Image Anal., vol. 56, pp. 122–139, 2

Dataset Link:

IDC: https://www.kaggle.com/datasets/paultimothymooney/breast-histopathology-images

Breakhis: https://www.kaggle.com/datasets/forderation/breakhis-400x

BACH: https://www.kaggle.com/datasets/dina0808/bach-icar-2018