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CERVICAL CANCER DETECTION USING HYBRID MODELS TECHNIQUES

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ABSTRACT Early location of cervical cancer is vital for progressing quiet results and diminishing mortality rates[1-2].This concept centers on a point-by-point technique for distinguishing and classifying cervical cell pictures utilizing profound learning models, connected to the SIPAKMED dataset, which comprises five unmistakable cervical cell categories[3-10].The preprocessing strategies utilized incorporate SLIC-based superpixel division and Canny edge location, which upgrade include extraction and make strides in classification precision[11-19].Different cutting-edge CNN models, such as ResNet50, VGG16, InceptionV3,Densenet121,Resnet 152 V2,and MobileNetV2, were fine-tuned and assessed.[20-22] Among these, the InceptionV3 demonstrated the most noteworthy precision of 92.19%, illustrating its viability in capturing complicated highlights at numerous scales[23-26].The preprocessing strategies played a noteworthy part in Moving forward, the model's execution is reflected in tall classification measurements over all categories.This comes about to show that such approaches can serve as an establishment for creating dependable and proficient demonstrative instruments, empowering precise and convenient discovery of cervical cancer, which is vital for early mediation and treatment[27-30].

KEYWORDS : ResNet50,VGG16,InceptionV3, Densenet121, Resnet52v2, and MobileNetV2.

INTRODUCTION

Cervical cancer remains one of the driving causes of cancer-related passouts among ladies universally, especially in low- and middle-income nations where access to opportune screening and therapeutic care is restricted. Early location of cervical cancer is basic because it essentially increments the chances of fruitful treatment and survival. In spite of the availability of screening tests just like the Pap spread, the manual translation of these tests can be time-consuming and inclined to mistakes. In this manner, there's a developing need for robotized, proficient, and precise strategies for identifying cervical anomalies in therapeutic pictures.

Recent headways in medical imaging and manufactured insights (AI) have made it conceivable to robotize and improve the precision of cervical cancer discovery. In particular, deep learning techniques like convolutional neural networks (CNNs) have shown great promise in the analysis of therapeutic images for the purpose of detecting and categorising abnormal cells. In this venture, we intend to use these headways by creating a profound learning-based classification demonstration for cervical cell pictures that makes strides upon existing strategies for superior precision and proficiency. Utilizing the freely accessible SIPaKMeD dataset, this considers centers on preprocessing microscopy pictures of cervical cells to make strides in highlight extraction and ensuing classification execution. To do so, we utilize progressed picture preparation strategies such as SLIC-based superpixel division, which breaks down complex cell structures into less difficult locales for way better investigation, and Canny edge discovery, which improves the clarity of cellular boundaries. The model's ability to distinguish between different phases and types of cervical deviations from the norm is advanced by these preprocessing processes. This project assesses a variety of state-of-the-art CNN models, counting ResNet50, VGG16, InceptionV3, EfficientNet, and MobileNet, to decide the most compelling demonstrate for classifying cervical cell pictures into five particular categories: dyskeratotic, Koilocytotic, metaplastic, Parab Koilocytotic Asal, and superficial-intermediate cells. By comparing these models on different execution measurements, such as precision, exactness, review, and F1-score, the ponder looks to recognize the ideal profound learning demonstrated for mechanized cervical cancer location. Through the integration of profound learning models and picture preprocessing methods, this investigation points to contributing to the advancement of a dependable, effective, and adaptable arrangement for early cervical cancer discovery, eventually supporting made strides screening and early intercession techniques. The following are the objectives of this project:Apply SLIC-based superpixel segmentation to effectively simplify and analyze complex cervical cell structures. The model's ability to distinguish between differentphases and types of cervical deviations from the norm is advanced by these preprocessing processes. Improved Boundary Detection: Employ edge detection techniques, such as Canny edge detection, to improve the clarity of cellular boundaries in microscopy images. Validate the models using the SIPaKMeD dataset and calculate their performance through metrics such as accuracy, precision, recall, and F1-score to identify the best-performing architecture.

The base paper [1] for this idea is titled "Profound Learning for Cervical Cancer Location utilizing Convolutional Neural Systems" by "A Ghoneim.". This work investigates the utilization of convolutional neural systems (CNNs) within the location of cervical cancer through restorative picture examination. The paper emphasizes the significance of effective highlight extraction to distinguish between unusual and ordinary cervical cells, which is vital for early location and conclusion. The creators highlight the ability of profound learning models, particularly CNNs, to memorize progressive highlights specifically from pictures, which essentially moves forward classification precision. This work lays a strong establishment for the current venture by displaying the potential of CNNs for cervical cancer discovery, which adjusts with the destinations of utilizing progressed profound learning techniques for progressed classification execution in cervical cell pictures.An outstanding headway within the field is the Semi-Supervised Cervical Unusual Cell Finder (SCAC) [2] displayed in "Z Zhang.". SCAC utilizes Transformer demonstration to capture long-range conditions inside cervical cell pictures, centering on unobtrusive but basic highlights that offer assistance in recognizing anomalies. Also, the paper presents USWA Expansion, a procedure that applies both solid and frail enlargements to upgrade preparing consistency. By leveraging a teacher-student demonstration for semi-supervised learning, the demonstration can produce pseudo-labels, empowering it to memorize from unlabeled information viably. SCAC assists in coordinating the Worldwide Versatile Highlight Pyramid Arrange (GAFPN) to extricate multi-scale highlights, which enhances the model's capacity to distinguish cervical anomalies at shifting scales. This paper is exceedingly pertinent to the current investigation, because it combines progressed methods like Transformers and semi-supervised learning to progress cervical cancer location.

In a comparable vein, CervixNet: Profound Learning and Advanced Twin System [3] by " V Sharma " takes a special approach by combining real-time information following with Advanced Twin innovation to persistently upgrade a virtual representation of the persistent. They demonstrate coordinating Repetitive Neural Systems (RNNs) and Bolster Vector Machines (SVMs) to classify cervical cancer cells, leveraging transient conditions within the information. The utilize of Foremost Component Examination (PCA) for dimensionality decrease improves computational effectiveness, which is significant for large-scale clinical applications. This approach permits for personalized following and prescient investigation, advertising an all-encompassing see of a patient's cervical wellbeing over time. This paper is especially profitable because it illustrates a novel integration of real-time checking with profound learning for cervical cancer discovery.Another critical commitment is the DSA-FFOGNet (Dual-Stream Self-Attention Arrange)[4] by " P Jiang ", which points to move forward symptomatic exactness by centering on significant locales inside complex cervical cell pictures. The demonstrate utilizes Self-Attention to specifically concentrate on vital highlights, improving the network capacity to identify unpretentious variations from the norm. The integration of a Way Conglomeration Arrange (Dish) makes a difference total multi-scale highlights, making the demonstrate strong to varieties in include sizes. Moreover, the show consolidates Beginning Gathering Misfortune, a domain-specific misfortune work that diminishes misclassifications by consolidating biomedical information. This work contributes to the extend by centering on fine-grained include extraction and consideration components, both of which are basic for exact cervical variation from the norm location.

The MaxCerVixT: Vision Transformer for Real-Time Discovery [5] by " I Pacal " presents an optimized demonstrate for quick and precise cervical cancer discovery, especially for restorative pictures with restricted information. The paper employs the MaxViT Spine to capture basic highlights from cervical cancer pictures and coordinating GRN-based Multi-Layer Perceptron's (MLPs) for better generalization over different persistent information. The show moreover utilizes Exchange Learning to adjust pre-trained models to cervical cancer discovery, viably leveraging information from bigger datasets. This approach is profoundly advantageous for real-time discovery in clinical situations, a highlight that's basic for convenient and exact conclusion in cervical cancer cases.

Further improving the field of cervical cancer location, the CNN-Based Prescient Show Utilizing VGG-16 & Colposcopy [6] by " N Youneszadeh " presents a strategy that combines the control of VGG-16, a well-known CNN engineering, for include extraction in colposcopy pictures. The utilize of Exchange Learning makes a difference relieve the require for huge labeled datasets, which is frequently a restriction in therapeutic imaging. Furthermore, Information Expansion procedures, such as picture revolution and flipping, are utilized to advance improve the models strength, permitting it to generalize superior over diverse picture varieties. This model is pertinent because it targets colposcopy pictures, which are habitually utilized in cervical cancer screenings, and illustrates the significance of information increase in progressing show execution.

The Unified Learning (FL) with CNNs for Privacy-Preserving Cervical Cancer Location [7] by " NSJoynab " addresses a basic issue in healthcare: preserving quiet protection whereas collaborating on data-driven arrangements. By utilizing Decentralized Preparing, person healing centers can prepare nearby models on them possess information, guaranteeing that touchy understanding data remains private. The paper moreover presents Combined Averaging (FedAvg) to total demonstrate upgrades from distinctive teach, subsequently moving forward the worldwide show without the required for information sharing. This combined learning system is particularly valuable in scenarios where security concerns are fundamental, and it guarantees that the model benefits from assorted datasets whereas keeping up information privacy.

The CTIFI: Three-Image Highlight Integration Demonstrate [8] by " T Xu " takes a diverse approach by joining different picture sorts to progress cervical cancer discovery. By utilizing SE-DenseNet as the spine, the show extricates highlights from saline, acidic acid, and iodine-treated pictures, which highlight distinctive symptomatic points of interest. The features from these pictures are at that point combined to supply a more comprehensive understanding of the cell's condition, upgrading classification precision. This work contributes to the venture by illustrating the potential of multi-modal imaging and includes integration for made strides cervical cancer determination.

The Gazelle Optimization with MobileNetv3 model [9] by " MK Nour " offers a lightweight and optimized arrangement for cervical cancer location, particularly in low-resource situations. By applying Gazelle Optimization to fine-tune the MobileNetv3 engineering, the demonstrate gets to be more effective, making it appropriate for versatile gadgets and circumstances where computational assets are restricted. Furthermore, the integration of a Stacked Extraordinary Learning Machine (SELM) Classifier Advance upgrades the model's classification exactness. This work is especially important for growing cervical cancer screening capabilities in resource-constrained settings.

Finally, the GAN & EfficientNet for Information Increase system [10] by "PM Shah" addresses the issue of restricted information by utilizing generative antagonistic systems (GANs) to create manufactured pictures. These pictures are at that point utilized to increase the dataset, making a difference that the demonstrate generalize superior to modern, concealed cases. EfficientNet, a high- performance demonstrate known for its precision and computational proficiency, is modeling these pictures. The integration of Exchange Learning encourages upgrades the model's capacity to use pre-trained information for cervical cancer discovery. This approach straightforwardly addresses the issue of information shortage, which could be a common challenge in therapeutic picture classification.

The FPNC (Fusion-Purification Arrange) [11] by " T Yang" presents a progressed classification demonstration that combines highlight extraction and accuracy improvement strategies to make strides toward demonstrative exactness. By utilizing a two-branch engineering, the demonstration captures both micro-level (surface) and macro-level (structure) highlights from cervical cell images. These highlights are at that point melded employing a bilinear pooling blender and decontaminated through a cross-branch decontamination module (CBPM) to evacuate unimportant data. This prepare refines the highlight set and upgrades the model's generally classification capability, advertising a more exact symptomatic apparatus for cervical cancer location. Finally, MSENet: Outfit CNN Demonstrate for Determination [12] by "R Pramanik" makes strides in forecast precision by combining numerous CNN models, counting Xception, Initiation V3, and VGG-16, in an ensemble framework. This gathering approach totals probabilities from distinctive models to make the ultimate forecast more dependable. Moreover, the paper talks about the utilization of information expansion methods, such as arbitrary turning, zooming, and flipping, to improve the prepared dataset and progress show generalization. This approach prepared the venture by illustrating the control of outfit learning and different designs in moving forward demonstrate exactness. These ponders collectively shape the establishment of the current inquiry, giving important experiences into different strategies utilized in cervical cancer location. The integration of profound learning models progressed Highlight extraction strategies, information enlargement, privacy-preserving systems, and multi-modal imaging approaches all contribute to the objective of creating a vigorous and productive framework for cervical cancer location and determination.

RELATED WORK

The suggested system, operational procedures, and software specifics are covered in this chapter.The following Figure 1 shows the system architecture of this project.

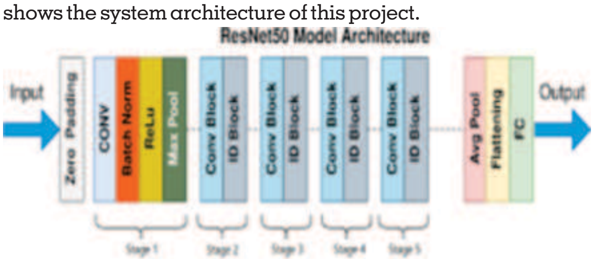

Figure 1. ResNet-50 Architecture

It outlines the structure of ResNet-50, exhibiting the convolutional layers, remaining pieces, character pieces, and completely associated layers utilized for highlight extraction and classification. The engineering of the proposed framework leverages the ResNet-50 show, which is broadly utilized for picture classification errands, especially for restorative picture investigation due to its strong include extraction capabilities. The graph outlines the engineering of ResNet-50,which comprises a few basic components: convolutional squares, character squares, leftover associations, and completely associated (FC) layers.ResNet-50 may be a profound convolutional neural organization (CNN) show with 50 layers outlined to handle the vanishing angle issue by utilizing residual connections. These associations permit the show to memorize the character mapping (i.e., the input being passed unaltered through the arrange), making it simpler to prepare more profound systems by easing the issue of slope corruption. The show begins with a beginning convolutional layer takenafter by an arrangement of pieces orchestrated in five stages, where generalization capacity and guarantee way better execution on each arrange contains convolutional squares and personality pieces. inconspicuous information. The show was prepared for 10 ages, where Each convolutional square applies several layers of convolutions, group early halting was utilized to stop preparing if the approval misfortune normalization, and enactment capacities (ReLU) to memorize and ceased progressing, in this way maintaining a strategic distance from extricate highlights from the input picture. The character squares superfluous computations and overfitting.In conclusion, the ResNet-50 contain leftover associations that specifically interface the input of the design, with its advanced plan and vigorous extraction control, shapes square to its yield, which makes strides in learning productivity, the spine of the proposed framework. By focusing on this base show, particularly as the profundity of the arrange increments. Normal the venture points to setting up a solid establishment for cervical cancer pooling is used to reduce the spatial measurements of the include maps location, whereas also giving a benchmark for comparison with other at the end of the engineering process. After being flattened into a progressed designs.

Vector, the yield is subsequently classified by passing it through a fullyassociated (FC) layer. The ultimate layer yields the predicted class.

RESULT ANALYSIS

The results of using the suggested model are shown inname, based on the highlights learned by the arrange. In this project, this part, along with a comparison of the effectiveness of variousResNet-50 is utilized as the primary base model for classifying cervical architectures and a discussion of how preprocessing methodscell pictures into numerous categories, which may be a basic errand for affect classification accuracy. As appeared within the bar charts cervical cancer detection. The model is well-suited for the task at hand produced from the exploratory comes about, the InceptionV3due to its depth and ability to capture both high-level and low-level demonstrated the most elevated execution, accomplishing an highlights. The leftover associations empower the show to memorize exactness of 94.19%. This result proposes that the InceptionV3more profound highlights whereas avoiding execution debasement, demonstrated, with its complex design and more profound layers, which is frequently a challenge when utilizing exceptionally profound was way better prepared to memorize complicated highlights fromsystems. This engineering has been chosen as the standard since of its the cervical cell pictures and shown in figures below . It demonstrated victory in picture classification assignments over an outperformed other models such as ResNet50 and EfficientNetB7, assortment of spaces, counting therapeutic picture examination. The which accomplished accuracy of 92.79% and 92.19%, ResNet-50 demonstrate is to begin with prepared on the preprocessed respectively. The ResNet50 show, being the primary base show cervical cell pictures, leveraging the profundity of the organization to utilized in our thinking, too appeared solid execution.

Whereas extricate significant highlights that contribute to precise classification. This incorporates highlights like cell shape, surface, and measure that marginally less exact than InceptionV3, its design still gives noteworthy results, particularly in identifying irregular and are basic for recognizing between diverse cell sorts orordinary cells with a great adjustment of accuracy and review. The anomalies. Although other models were investigated amid the project, EfficientNetB7 show, known for its effectiveness in dealing with such as VGG-16, InceptionNet, and MobileNet, ResNet-50 was chosen as the essential demonstration due to its adjustment of profundity and effectiveness. The other models were compared based on exactness, computational assets, illustrated competitive exactness whereas keeping up a generally smaller show estimate. The impact of many metrics, including precision, review, and f1-score, for eachexecution, and computational prerequisites. In spite of the promising demonstration is also highlighted by the bar charts. These comes about from other designs, ResNet-50 performed the finest, given measurements were utilized to assess how well the models took its profound structure and remaining learning capabilities, which were care of both positive and negative classes. The InceptionV3 showsbasic in distinguishing unpretentious highlights in cervical pictures. The input layer of the show acknowledges pictures, with the measurements not as it were accomplished the most noteworthy exactness but moreover illustrated predominant values in accuracy and review, characterized as stature, width, and profundity. For grayscale pictures, affirming its unwavering quality for the classification assignment. The profundity is 1, and for color pictures, the profundity is 3.

The exactness and review scores for ResNet50 and EfficientNetB7engineering is based on a pre-trained Completely Convolutional were comparable, in spite of the fact that they were somewhat Organize (FCN) utilizing ResNet50 as the spine for include extraction. Lower than InceptionV3. SLIC division and Canny edge The ultimate convolutional layer has been altered to yield 2 classes, localisation, two preprocessing techniques, were essential in comparing to abnormal and typical conditions within the cervical cell enhancing the model's ability to discriminate between abnormalpictures. With a clump estimate of 32 and a learning rate of 0.0001, the and normal cells. These preprocessing techniques advanced the Adam optimizer is used to prepare the show. For multi-class categorization, the categorical cross-entropy misfortune work is differentiation between the two groups as described in the results. For all models, the Recipient Working Characteristic Zoneemployed. Dropout layers and L2 regularization were used to refine the Beneath Bend (ROC-AUC) scores were fundamentally high (> model in order to prevent overfitting, especially after observing 0.90), indicating that the preprocessing techniques were effective problems with generalization. Information increase procedures are in enhancing demonstration execution.

Utilized, counting and resizing the input pictures to 224x224 pixels and performing picture normalization (scaling pixel values to a run of 1).These procedures were connected to make strides in the model's.

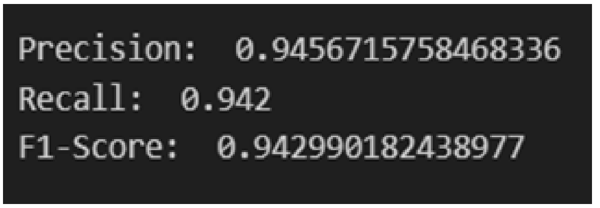

Figure1: Precision, recall, and F1-score

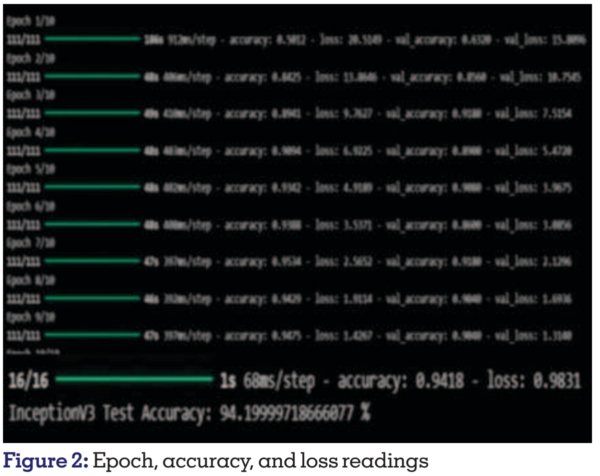

Figure 2: Epoch, accuracy, and loss readings

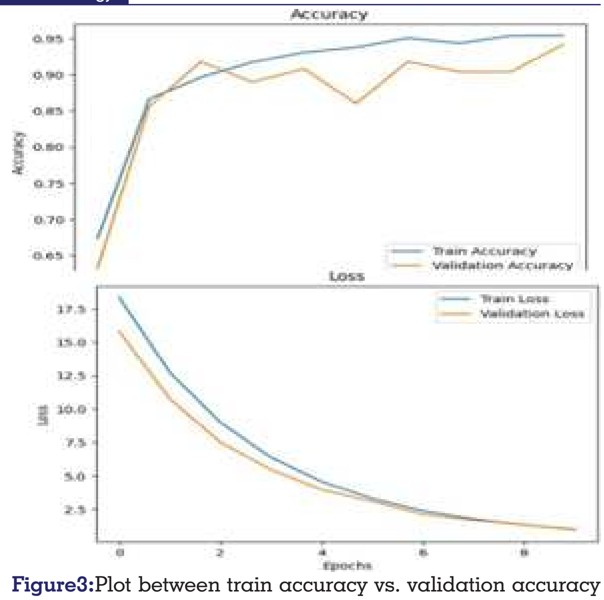

Figure3: Plot between train accuracy vs. validation accuracy and train loss and validation loss

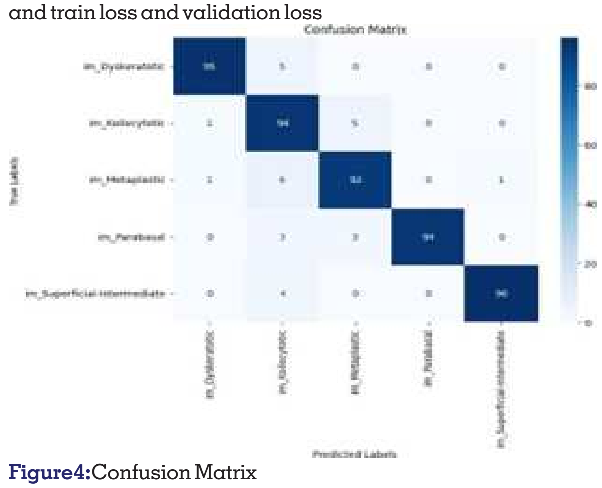

Figure4: Confusion Matrix

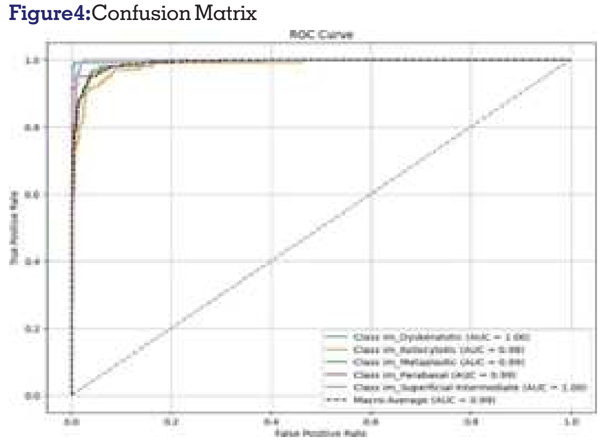

Figure5:ROC curve

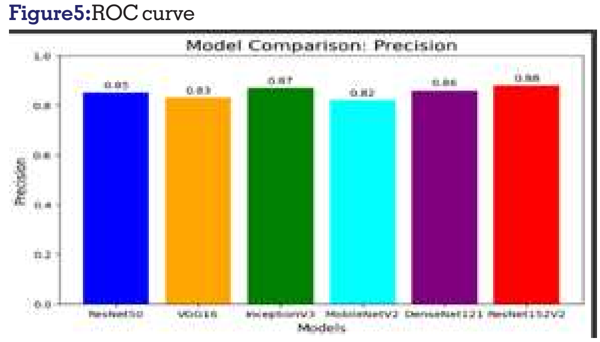

Figure:6(a) precision

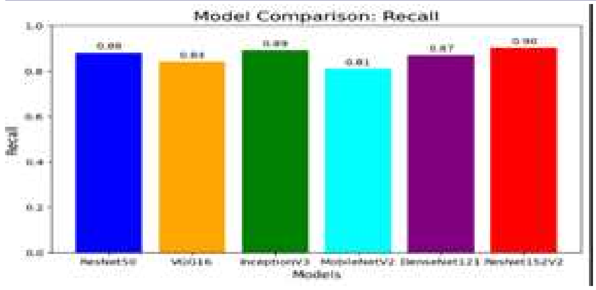

Figure:6(b) Recall

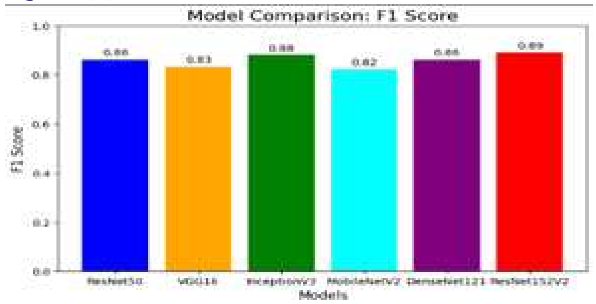

Figure:6(c) F1_score

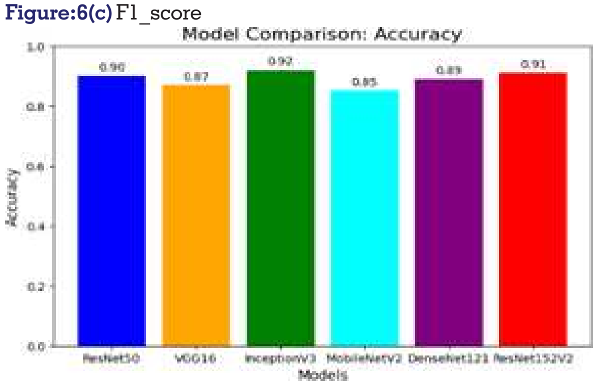

Figure:6(d) Accuracy

CHALLENGES

Limited access to timely screening and therapeutic care, particularly in low- and middle-income countries, contributes to cervical cancer being a leading cause of cancer-related deaths among women globally. This highlights a significant healthcare infrastructure challenge that technology aims to address.

The traditional manual interpretation of screening tests like the Pap smear can be time-consuming and prone to errors. This inefficiency and potential for human error necessitate the development of automated and more accurate methods.

While deep learning models show great promise, the project itself encountered challenges such as overfitting, which they addressed using dropout layers and L2 regularization. This is a common challenge in training deep learning models, especially with medical image data. The fact that they observed "problems with generalization" further underscores this challenge,

where a model performs well on training data but poorly on unseen data.

The need for preprocessing techniques like SLIC-based superpixel segmentation and Canny edge detection suggests that the raw microscopy images of cervical cells present challenges for direct feature extraction and classification. These preprocessing steps are crucial to enhance feature clarity and improve model performance.

The SIPaKMeD dataset, while valuable, might be a subset of a larger database. This raises a potential challenge regarding the size and representativeness of the training data. Furthermore, the single-cell photos in the dataset are mentioned as being "altered for testing purposes", which could be a limitation in how well the models trained on this data generalize to completely unseen, unaltered clinical images. The availability of only 500 unseen data points for assessing model performance might also be considered a limitation in comprehensively evaluating the models' robustness.

The necessity of gathering more diverse data from different sources to improve the models' generalization and robustness, especially for rare cases.

The potential benefit of testing more advanced or hybrid models, including ensemble methods, to further enhance accuracy and robustness. This implies that current models, while achieving high accuracy, still have room for improvement.

The critical need to validate the models in real-world clinical settings to ensure their practical applicability, safety, and effectiveness for patient use. Translation from research settings to clinical practice often involves unforeseen challenges.

The desirability of expanding the models for real-time detection and diagnosis, suggesting that current implementations might not yet be optimized for such immediate applications.

The importance of developing methods for model explainability (like Grad-CAM or SHAPE) to enhance trust and interpretability, which is particularly crucial in medical applications where understanding the model's reasoning is vital for clinicians. The "black box" nature of deep learning models can be a challenge for their adoption in clinical practice.

GAPS

There are numbered items (1 through 6) that seem to be titles or descriptions of results but lack the actual content or the plots they refer to. For example, item "1. Epoch, accuracy and loss readings:" is a title but does not provide any actual readings. Similarly, "2. Plot between train accuracy vs validation accuracy and train loss and validation loss:" describes a plot that is not shown. The same applies to "3. Confusion Matrix:", "4. ROC curve:", "5. Precision, Recall and F1-score:", and "6. Bar plot to compare Precision, Recall,

F1-score and Accuracy:". The subsequent paragraph starting with "As appeared within the bar charts produced from the exploratory comes about..." likely refers to the missing bar plot in item 6.

The text mentions specific accuracy values achieved by different models: **InceptionV3 achieved an accuracy of 92.19%**, **ResNet50 achieved 80.79% accuracy**, and **Densenet 121 achieved 90.19% accuracy**. These values likely would have been visually represented in the missing plots and potentially listed under item 5.

he text states that "The impact of many metrics, including precision, review, and f1-score, for each demonstration is also highlighted by the bar charts". However, these bar charts are not present. The subsequent sentences discuss these metrics for InceptionV3, ResNet50, and Desnenet121 implying these details were meant to be included under item 5 and visualized in item 6.

The text mentions that "For all models, the Recipient Working Characteristic Zone Beneath Bend (ROC-AUC) scores were fundamentally high (> 0.90)", which would likely have been detailed and visualized in item 4.

The code includes comments indicating plots of accuracy and loss over epochs, confusion matrices, ROC curves, and classification reports for each model (ResNet50, VGG16, InceptionV3, EfficientNetB0, EfficientNetB7, MobileNetV2, MobileNetV3). However, the actual output of these plots and reports (which would visually fill the gaps in Chapter 3) is not provided in the text, only the Python code to generate them. Similarly, the code calculates and prints precision, recall, and F1-scores for each model.

CONCLUSION

Using various designs, including InceptionV3, ResNet50, and DenseNet121, we successfully developed and evaluated a deep learning-based demonstration for the classification of cervical cancer cells. The test results showed that InceptionV3 outperformed ResNet50 (92.79%) and EfficientNetB7 (92.19%) with the highest exactness of 94.19%. The utilization of preprocessing strategies, counting SLIC division and Canny edge discovery, played a significant part in progressing the models' capacity to distinguish between ordinary and irregular cervical cells. These procedures upgraded the distinctness between the two classes and brought about solid ROC-AUC scores (>0.90) for all models. The findings indicate that the selected models, especially InceptionV3, are powerful tools for cervical cancer categorisation that may aid in early detection.While the current results are promising, there are several areas for future improvement and exploration. Future work can center on gathering more differing information from distinctive sources to move forward the models generalization and vigor, especially for edge cases or uncommon occasions of irregular cells. Testing with more Progressed or crossbreed models, such as gathering models, seem to offer assistance in advance upgrade exactness and robustness. It is vital to approve the demonstration in real-world clinical settings to evaluate its viable appropriateness and guarantee its security and adequacy for understanding use. The demonstration might be expanded for real-time location and conclusion, possibly joining it into existing therapeutic imaging frameworks for speedier, mechanized analysis. Creating strategies to show explain ability (e.g., utilizing Grad- CAM or SHAP) might upgrade belief and interpretability, which is imperative for therapeutic applications.

REFERENCES

1. Ghoneim, A., Muhammad, G., & Hossain, M. S. (2020). Cervical cancer classification using convolutional neural networks and extreme learning machines. Future Generation Computer Systems, 102, 643-649.
2. Zhang, Z., Yao, P., Chen, M., Zeng, L.,Shao, P., Shen, S., & Xu, R. X. (2024). SCAC: A Semi-Supervised Learning Approach for Cervical Abnormal Cell Detection. IEEE Journal of Biomedical and Health Informatics.
3. Sharma, V., Kumar, A., & Sharma, K. (2024). Digital twin application in women's health: cervical cancer diagnosis with CervixNet. Cognitive Systems Research, 87, 101264.
4. Jiang, P., Liu, J., Feng, J., Chen, H., Chen, Y., Li, C.,... & Cao, D. (2024). Interpretable detector for cervical cytology using self-attention and cell origin group guidance. Engineering Applications of Artificial Intelligence, 134, 108661.
5. Pacal, I. (2024). MaxCerVixT: A novel lightweight vision transformer-based approach for precise cervical cancer detection. Knowledge-Based Systems, 289, 111482.
6. Youneszadeh, N., Marjani, M., & Ray, S. K. (2023). A predictive model to detect cervical diseases using convolutional neural network algorithms and digital colposcopy images. IEEE Access, 11, 59882-599898.
7. Joynab, N. S., Islam, M. N., Aliya, R. R., Hasan, A. R., Khan, N. I., & Sarker, I. H. (2024). A federated learning-aided system for classifying cervical cancer using PAP-SMEAR images. Informatics in Medicine Unlocked, 47, 101496.
8. Xu, T., Liu, P., Wang, X., Li, P., Xue, H., Jin, W.,... & Sun, P. (2023). CTIFI: Clinical-experience- guided three-vision images features integration for diagnosis of experience-related lesions. Biomedical Signal Processing and Control, 80, 104235.
9. Nour, M. K., Issaoui, I., Edris, A., Mahmud, A., Assiri, M., & Ibrahim, S. S. (2024). Computer-aided cervical cancer diagnosis using a gazelle optimization algorithm with a deep learning model. IEEE Access.
10. Shah, P. M., Ullah, H., Ullah, R., Shah, D., Wang, Y., Islam,S. U.,... & Rodrigues, J. J. (2022). DC-GAN-based synthetic X-ray image augmentation for increasing the performance of EfficientNet for COVID-19 detection. Expert systems, 39(3), e12823.
11. Yang, T., Hu, H., Li, X., Meng, Q., Lu, H., & Huang, Q. (2024). An efficient Fusion-Purification Network for Cervical Pap-Smear Image Classification. Computer Methods and Programs in Biomedicine, 251, 108199.
12. Pramanik, R., Banerjee, B., & Sarkar, R. (2023). MSENet: Mean and standard deviation-based ensemble network for cervical cancer detection. Engineering Application of Artificial Intelligence, 123, 106336.
13. Plissit, M. E., Dimitrakopoulos, P., Sfikas, G., Nikou, C., Krikoni, O., & Charchanti, A. (2018, October). Sipakmed: A new dataset for feature- and image-based classification of normal and pathological cervical cells in paimage-basedges. In the 2018 25th IEEE international conference on image processing (ICIP) (pp. 3144-3148). IEEE.
14. Arya, M., Mittal, N., & Singh, G. (2020). Three segmentation techniques to predict the dysplasia in cervical cells in the presence of debris. Multimedia Tools and Applications, 79(33), 24157-24172.
15. Razavi, R., Bemani, A., Baghban, A., Mohammadi, A. H., & Habibzadeh, S. (2019). An insight into the estimation of fatty acid methyl ester based biodiesel properties using a LS SVM model. Fuel, 243, 133-141.
16. DTU/Herlev Pap Smear Database. (2008). http://mde-lab.aegean.gr/index.php/downloads
17. Kurman, R., Solomon, D.: The Bethesda System for Reporting Cervical/Vaginal Cytologic Diagnoses. Springer-Verlag, New York (1994)
18. Liu, Y., Zhao, T., Zhang, J.: Learning multispectral texture features for cervical cancer detection. In: Proc. Int. Symp. Biomedical Imaging. (2002) 169–172..
19. Cristianini, N., Shawe-Taylor, J.: An Introduction to Support Vector Machines. Cambridge University Press, Cambridge, UK (2000)..
20. Blum, A., Langley, P.: Selection of relevant features and examples in machine learning. Artificial Intelligence 97 (1997) 245–271.
21. Parkin DM, Bray F, Ferlay J, et al (2005). Global cancer statistics, 2002. CA Cancer J Clin, 55, 74-108.
22. Patil S, Moafa IH, Mosa Alfaifi M, et al (2020). Reviewing the role of artificial intelligence in cancer. Asian Pac J Cancer Biol, 5, 189-99.
23. Ramnath GS, Harikrishnan R (2021). Households electricity consumption analysis: a bibliometric approach. Libr Philos Pract, 5098. https://digitalcommons.unl.edu/ libphilprac/5098.
24. Ramondetta L (2013). What is the appropriate approach to treating women with incurable cervical cancer?. J Natl Compr Canc Netw, 11, 348-55.
25. M. A. Abu-Lubad, A. J. Dua'a, G. F. Helaly et al., "Human Papillomavirus as an Independent Risk Factor of Invasive Cervical and Endometrial Carcinomas in Jordan," Journal of Infection and Public Health, vol. 13, no. 4, pp. 613-618, 2022.
26. B. Obeidat, I. Matalka, A. Mohtaseb et al., "Prevalence and Distribution of High-risk Human Papillomavirus Genotypes in Cervical Carcinoma, Low-grade and High-grade Squamous Intraepithelial Lesions in Jordanian Women," European Journal of Gynaecological Oncology, vol. 34, no. 3, pp.
27. Solid State Technology, vol. 63, no. 2s, pp. 9896-9909, 2020.
28. R. Alazaidah, F. A. Ahmad, M. F. M. Mohsin and W. A. AlZoubi, "Multi-label Ranking Method Based on Positive Class Correlations," Jordanian Journal of Computers and Information Technology (JJCIT), vol. 6, no. 4, pp. 377-391,2020.
29. M. Alluwaici, A. K. Junoh and R. Alazaidah, "New Problem Transformation Method Based on the Local Positive Pairwise Dependencies among Labels," Journal of Information & Knowledge Management, vol. 19, no. 1, ID. 2040017, 2020.
30. Anon 2018, "Improve Your Model Perfor- mance using Cross Validation (in Python / R)", An-f10ba6e38234>.
31. Anon 2018, " Google ML", Blog, viewed 26 May, 2018,< https://www.guru99.com/r-generalized- linear-model.html>.
32. Mishra, A. (2018, February 24). Metrics to Evaluate your Machine Learning Algorithm. Retrieved from https://towardsdatascience.com/metrics-to-evaluate-your-mac hine-learning-algorithm-f10ba6e38234
33. Narkhede, Sarang. "Understanding Confusion Matrix – Towards Data Science." Towards Data Science, Towards Data Science, 9 Feb. 2018, towardsdatascience.com/understanding-confusion-matrix-
34. A. L. Buczak and E. Guven, "A survey of data mining and machine learning methods for cyber security intrusion detection," IEEE Commun. Surveys Tuts., vol. 18, no. 2, pp. 1153–1176, 2nd Quart., 2016.
35. I. J. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville, and Y. Bengio, "Generative adversarial net-works," 2014, arXiv:1406.2661. [Online]. Available: https://arxiv.org/ abs/1406.2661
36. E. C. Ferrer, "The blockchain: A new framework for robotic swarm systems," 2017, arXiv:1608.00695. [Online]. Available: https://arxiv.org/ abs/1608.00695
37. J. Benet, "IPFS—Content addressed, Versioned, P2P file system," 2014, arXiv:1407.3561. [Online]. Available: https://arxiv.org/abs/1407.3561
38. G. Wood, "Ethereum: A secure decentralised generalised transaction ledger," Ethereum Project Yellow Paper, 2018. Accessed: Jun. 5, 2019. [Online]. Available: https://ethereum.github.io/yellowpaper/paper.pdf
39. E. Nashar, M. Ahmed, R. Y. Bamjboor, A. Mansour, and B. A. Althobaity, "Awareness of the women about vaginal infection as a risk factor for cervical cancer in Taif city," Int. J. Med. Dev. Countries, vol. 4, pp. 2108–2114, 2020.
40. Alghamdi, M.; Al-Mallah, M.; Keteyian, S.; Brawner, C.;Ehrman, J.; Sakr, S. Predicting diabetes mellitus using SMOTE and ensemble machine learning approach: The Henry Ford ExercIse Testing (FIT) project. PLoS ONE 2017, 12, e0179805.
41. Pang-Ning, T.; Steinbach, M.; Kumar, V. Introduction to Data Mining; Pearson Addison-Wesley: Boston, MA, USA, 2006.
42. Chandrashekar, G.; Sahin, F. A survey on feature selection methods q. Compute. Electr. Eng. 2014, 40, 16–28.
43. Alonso-Betanzos, A. Filter Methods for Feature Selection–A Comparative Study; Springer: Berlin/Heidelberg, Germany, 2007.
44. Peng, Y.; Wu, Z.; Jiang, J. A novel feature selection approach for biomedical data classification. J. Biomed. Inform. 2010, 43, 15–23.
45. Chen, X.; Jeong, J.C. Enhanced Recursive Feature Elimination. In Proceedings of the Sixth International Conference on Machine Learning and Applications, Cincinnati, OH, USA, 13–15 December 2007; pp. 429–435.
46. Go, J.; Łukaszuk, T. Application of The Recursive Feature Elimination And The Relaxed Linear Separability Feature Selection Algorithms To Gene Expression Data Analysis. Adv. Computer. Sci. Res. 2013, 10, 39–52.
47. Van Ha, S.; Nguyen, H. FRFE: Fast Recursive Feature Elimination for Credit Scoring FREE: Fast Recursive Feature Elimina-Computer. Sci. Appl. 2016, 7, 148–157.
48. Ahmed, M.; Kabir, M.M.K.; Kabir, M.; Hasan, M.M. Identification of the Risk Factors of Cervical Cancer Applying Feature Selection Approaches. In

Proceedings of the 3rd International Conference on Electrical, Computer & Telecommunication Engineering ICECTE 2019, Rajshahi, Bangladesh, 26–28 December 2019; pp. 201–204.
49. Hamada, M.; Tanimu, J.J.; Hassan, M.; Kakudi, H.A.; Robert,P. Evaluation of Recursive Feature Elimination and LASSO Regularization-based optimized feature selection approaches for cervical cancer prediction. In Proceedings of the 2021 IEEE 14th International Symposium on Embedded Multicore/Many-Core Systems-on-Chip (MCSoC), Singapore, 20–23 December 2021; pp. 333–339.
50. Rodriguez-galiano, V.F.; Luque-espinar, J.A.; Chica-olmo, M.; Mendes, M.P. Feature selection approaches for predictive modelling of groundwater nitrate pollution: An evaluation of filters, embedded and wrapper methods. Sci. Total Environ. 2018, 624, 661–672.
51. Tibshirani, R. lasso.pdf. J. R. Stat. Soc. 1996, 58, 267–288.
52. Yamada, M.; Wittawat, J.; Leonid, S.; Eric, W.P.; Masashi, S. High-Dimensional Feature Selection by Feature-Wise Kernelized Lasso. Neural Comput. 2014, 207, 185–207.
53. Ghosh, P.; Azam, S.; Jonkman, M.; Karim, A.; Shamrat, F.M.J.M.; Ignatious, E.; Shultana, S.; Beeravolu, A.R.; De Boer, F. Efficient
54. More, A. Survey of resampling techniques for improving classification performance in unbalanced datasets. arXiv 2016, arXiv:1608.06048.
55. Goel, G.; Maguire, L.; Li, Y.; McLoone, S. Evaluation of Sampling Methods for Learning from Imbalanced Data. In Intelligent Computing Theories; Springer: Berlin/Heidelberg, Germany, 2013; pp. 392–401.
56. Chen, T.; Shi, X.; Wong, Y.D. Key feature selection and risk prediction for lane-changing behaviors based on vehicles' trajectory data. Accid. Anal. Prev. 2019, 129, 156–169.
57. Zeng, M.; Zou, B.; Wei, F.; Liu, X.; Wang, L. Effective prediction of three common diseases by combining SMOTE with Tomek links technique for imbalanced medical data. In Proceedings of the 2016 IEEE International Conference of Online Analysis and Computing Science (ICOACS), Chongqing, China, 28–29 May 2016; pp. 225–228.
58. William, W.; Ware, A.; Basaza-ejiri, A.H.; Obungoloch, J. A review of image analysis and machine learning techniques for automated cervical cancer screening from pap-smear images. Computer. Methods Programs Biomed. 2018, 164, 15–22.
59. Yamashita, R.; Nishio, M.; Do, R.K.G.; Togashi, K. Convolutional neural networks: An overview and application in radiology. Insights Imaging 2018, 9, 611–629.
60. Ijaz, M.F.; Attique, M.; Son, Y. Data-Driven Cervical Cancer Prediction Model with Outlier Detection and Over-Sampling Methods. Sensors 2020, 20, 2809.
61. Saxena, R. Building Decision Tree Algorithm in Python with Decision Tree Algorithm Implementation with Scikit Learn How We Can Implement Decision Tree Classifier. 2018, pp. 1–16. Available online: https://dataaspirant.com/decision-tree-algorithm-python-with- scikit-learn/ (accessed on 1 February 2017).
62. Patel, R.; Aluvalu, R. A Reduced Error Pruning Technique for Improving Accuracy of Decision Tree Learning. Int. J. Adv. Sci. Eng. Inf. Technol. 2014, 3, 8–11.
63. Patil, D.D.; Wadhai, V.; Gokhale, J. Evaluation of Decision Tree Pruning Algorithms for Complexity and Classification Accuracy. Int. J. Comput. Appl. 2010, 11, 23–30.
64. Berrar, D. Cross-Validation. In Reference Module in Life Sciences; Elsevier: Amsterdam, The Netherlands, 2019.
65. Hassan, M. Smart Media-based Context-aware Recommender Systems for Learning: A Conceptual Framework. In roceedings ofAlbers DJ, Hripcsak G. Next-generation phenotyping of electronic health records. Journal of the American Medical Informatics Association. 2012; 20(1):117–121. https://doi.org/10.1136/amiajnl-2012- 001145 PMID: 22955496
66. Jensen PB, Jensen LJ, Brunak S. Mining electronic health records: towards better research applications and clinical care. Nature Reviews Genetics. 2012; 13(6):395. https://doi.org/10.1038/nrg3208 PMID:
67. diction models with electronic health records data: a systematic review. Journal of the American Medical Informatics Association. 2017; 24(1):198–208. https://doi.org/10.1093/jamia/ocw042 PMID: 27189013
68. Staf C, Högberg T, Rosenberg P, Dahm-Kähler P, Bergmark K. Svenska Kvalitetsregistret för Gynekologisk Cancer -Årsrapport 2017. Regionalt cancercentrum väst 2017.
69. SBU. Tidig upptäckt av symtomgivande cancer. En systematisk litteraturöversikt. Statens beredning för medicinsk utvärdering (SBU), 2014.
70. Zhao D, Weng C. Combining PubMed knowledge and EHR data to develop a weighted Bayesian net- work for pancreatic cancer prediction. Journal of biomedical informatics. 2011; 44(5):859–868. https:// doi.org/10.1016/ j.jbi.2011.05.004 PMID: 21642013