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CellInsight:AI-Powered Web Solution for Cervical Cancer Classification

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***Abstract*—This paper introduces the system, a Python-based web platform developed for the secure management, processing, and intelligent analysis of medical images and video streams. The system leverages the great libraries and frameworks of Python, especially Flask, in building the backend.Through the emphasis on AI model integration of TensorFlow/PyTorch for better detection accuracy and precision.For the healthcare pro- fessionals.The report provides information about the architecture of the platform, the key features of the system, and how integrating AI transforms diagnostic workflows. Results indicate the system as a scalable, user-friendly, and secure tool for the management of medical images in health settings. It addresses the problem of cervical cancer as a health burden, with increased importance for low- and middle-income countries. Early and precise classification of cervical.Proper classification of cancer subtypes is crucial to guide the treatment decisions and to improve patient outcomes in those regions. In an attempt to solve this problem, the system develops a centralized imaging framework-based model intended for cervical cancer diagnosis classification. This framework is developed based on state-of-the- art imaging modalities and artificial intelligence. It improves the diagnostic workflow with greater efficiency and accuracy. The system presents hybrid models that are based on a combination of ideas of convolutional neural networks and Gradient-boosted machine learning classifiers are utilized for robust and reliable performance in the classification of various subtypes of cervical cancer. The system also ensures security and centralization of data; hence, the healthcare professionals get to work on scalable and accurate tools for the classification process. All these have been developed through Python-based technologies and incorporated into AI and secure infrastructure to make the system a pivotal innovation in modern diagnostics.**

***Index Terms*—Medical image processing, AI in healthcare, cervical cancer diagnosis, deep learning, convolutional neural net- works (CNN), Gradient-boosted machine learning, TensorFlow, PyTorch, Flask, diagnostic workflow, secure medical imaging, intelligent analysis, centralized imaging framework, healthcare technology, AI-driven classification, medical video stream analy- sis.**

I. Introduction

Specifically, the system focuses on the types of cervical cancer and identifies crucial challenges facing diagnostic accuracy and workflow effectiveness.It remains one of the leading causes of cancer deaths in women worldwide, and low- and middle-income countries are especially adversely affected, mainly because screening and treatment that are effective remain inaccessible.According to the World HealthOrganization [1], there were about 604,000 new cases and 342,000 deaths from cervical cancer in 2020. Early detection of cervical cancer along with accurate typing of the cancers will guide proper treatment decisions for improving patient outcome. Cervical cancer is one of the major causes of death from cancer in women across the globe. It has a greater negative impact on low- and middle-income countries because access to effective screening and treatment is very limited. According to the [1] [2] report, there were approximately 604,000 new cases and 342,000 deaths due to cervical cancer in 2020.The early detection of cervical cancer and proper cat- egorization of cervical cancer types are important for Guiding Treatment Decisions and Improving Patient Outcomes. There is room for scalable, reliable, and generalizable AI-driven solutions since the traditional screening techniques, such as Pap smear and visual inspection with acetic acid, are usually non-quantifiable, inconsistent, and resource-dependent. AI-based classification models have transformed cervical cancer diagnosis with the large-scale dataset of SIPaKMeD. This dataset groups cervical cells into five categories, including dyskeratotic, koilocytotic, metaplastic, parabasal, and super- ficial intermediate cells. Among them, the most critical cells are dyskeratotic and koilocytotic because they reveal archi- tectural alterations caused by HPV that cause precancerous lesions. Identification of parabasal and superficial interme- diate cells is just as important, in order to minimize false positives and avoid unneeded medical intervention . Using well-balanced datasets and state-of-the-art AI techniques, the system is poised to improve reliability in diagnosis so that the system's classification will not be biased, especially for resource-poor settings where such cervical cancer screening is most necessary. This research introduces a centralized imaging framework with AI-based classification models to improve the limitations of traditional screening approaches. It integrates deep learning techniques with automated imaging workflows to enhance not only diagnostic accuracy but also streamlined medical imaging processes, hence facilitating mass screening programs. Inference of AI in cervical cancer classification may boost early detection rates, optimize treatment planning, and reduce mortality around the world.

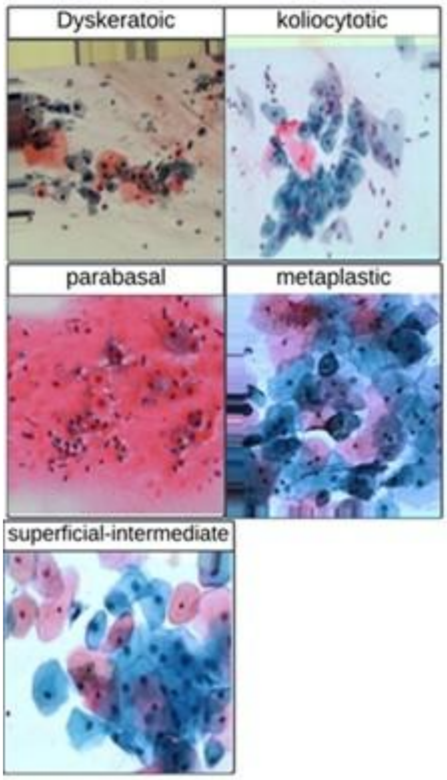


Fig. 1. Dataset

II. Literature Review

DeepPap: Deep Convolutional Networks for Cervical Cell Classification, where an attempt is made to classify cer- vical cells using deep learning. This paper has indicated the disadvantages associated with traditional approaches of classification as they depend entirely on accurate segmen- tation of cells and manually designed features [1] [3] [8]. Thus, they introduced a deep ConvNet trained from natural image databases and fine-tuned on the cervical cell images. The model directly classifies the cervical cells using patches centered at the nucleus with no segmentation, thus the new approach has resulted in a 98.3% classification accuracy on the Herlev Pap smear dataset, overcoming the previous work and showing a promise of the application of deep learning for automating cervical screening. In Comparing Deep Learning Models for Multi-cell Classification in Liquid-based Cervical Cytology Images discuss the possibility of using convolu- tional neural networks (CNNs) for automatic classification of cervical cytology images [4] [9]. They provide a method which generates labeled cervical patch data and extracts deep hierarchical features using CNNsTheir results show that the VGG-19 model performs the best for the classification of cervical cytology patches with 95% accuracy in the precision-recall curve.This study is based on the difficulties in cell seg- mentation due to clustered and overlapped cells and presents novel graph-based cell detection for better classification. [5]
[7] [10] presented in their paper ”MobileNetV2 Based CervicalCancer Classification Using Pap Smear Images” MobileNetV2 as an efficient deep learning model for cervical cancer classi- fication. The benefits of MobileNetV2 are high computational efficiency and effectiveness, making it ideal for deployment in resource-constrained environments. They divided their model into five classes, namely Superficial-Intermediate, Parabasal, Koilocytotic, Dyskeratotic, and Metaplastic, to achieve a 95% accuracy in classification. The paper calls for the role of auto- mated cervical cancer classification for better early detection and better treatment of patients. The paper titled ”Artificial intelligence strengthens cervical cancer screening – present and future” presents an overview of how artificial intelligence could be used in improving cervical cancer screening. It shows how AI, in particular deep learning, enhances the sensitivity and effectiveness of screening techniques by analyzing cervi- cal images and picking up abnormal cytology. The application of AI is more useful in low-resource environments since there are fewer trained health professionals. Other challenges still exist, such as risks of misdiagnosis, clinician mistrust, and regulatory approvals. The conclusion calls for further validation and research aimed at better ensuring effectiveness about the integration of AI into routine clinical practice.

III. Methodology

This research presents a web-based platform developed entirely using Python, designed to classify different types of cervical cancer from medical imaging data. The platform integrates a full-stack Python architecture, ensuring a seamless and efficient interaction between users, the AI processing system, and data management modules. The core components include a Python-based frontend, backend, and AI model integration, designed to provide a reliable and scalable solution for healthcare professionals in cervical cancer diagnostics.

A. Frontend:

The frontend is built using Flask, which serves both as the web framework for routing and as the structure for creating dynamic user interfaces. With Flask, Python manages the HTML templates (using Jinja2 template engine), CSS, and JavaScript to ensure a responsive, real-time interaction for users. Key frontend features include:

- Dynamic Form Handling: The platform utilizes Flask’s forms to enable healthcare professionals to upload cervi- cal cancer images and manage patient records with real- time validation and feedback.
- Interactive Dashboards: Jinja2 templates dynamically ren- der patient records, classification results, and medical images in an intuitive, easy-to-navigate dashboard format. Data visualization libraries, such as Plotly or Matplotlib, are employed to display AI-processed results clearly.
- Cross-Browser Compatibility: The frontend is optimized to work seamlessly across major web browsers and de- vices, ensuring healthcare professionals can access the platform from various environments. By using Python for both

backend and frontend, we maintain code simplicity

and consistency, ensuring tight integration between all components of the system.

B. Backend:

The backend structure relies on Flask and Flask-RESTful. It is an easy, clean, and flexible Python-based framework that provides a model for handling user interactions, managing data, and integrating AI models. The key functionality of the backend includes:

1) User Authentication and Authorization: Implementing secure user authentication using Flask-Login and Flask- Security, the system supports role-based access control (RBAC); thus, it prevents any unauthorized access to sensitive patient data and processed results by only allowing healthcare professionals.

2) API Layer: This brings a light and robust API layer on Flask-RESTful that would handle requests for patient data, uploading of images, and the initiation of AI processing workflows. All frontend-backend communications are handled through structured API endpoints.

3) Data Management: All the patient data and uploaded images are stored in either SQLite or PostgreSQL database, and SQLAlchemy ORM allows for real-time retrieval, thereby ensuring fast and secure access to the information.

4) Secure Data Transmission: All data exchange, be it up- loading images or retrieving AI results, is SSL/TLS encrypted so that the application strictly complies with all healthcare regulations, including HIPAA.

C. AI Models:

The AI models are integrated using Python libraries such as TensorFlow or PyTorch within a Flask-based microservice environment. The AI component of the platform applies deep learning techniques for classifying cervical cancer types from medical images. Key aspects of the AI model integration include:

1) Image Preprocessing: The cervical images that would be uploaded would be preprocessed, i.e., resized and normalized using the OpenCV and Pillow libraries so the AI model would work with normalized input data.

2) Cervical Cancer Classification:: It feeds preprocessed images to a trained CNN that classifies the images into cate- gories of cervical cancer. This model's accuracy and reliability are ensured by training it extensively on large cervical image datasets.

3) Model Inference and Results Display: The results are sent back to the frontend after completing classifications, and they are displayed live on the interactive dashboard. All kinds of images, both raw and processed, are stored in cloud storage (AWS S3) or saved locally using Flask-Uploads for future accessibility.

4) Efficient Data Storage: Patient metadata, including clas- sification results, timestamps, and other relevant information, is stored securely in th database for long-term tracking of diagnosis history.The platform is completely implemented in Python, using Flask as the major framework for the frontend and the back- end. This approach ensures the simplicity, scalability, and high performance of the system. With the AI models developed using powerful deep learning libraries in Python, we can get robust cervical cancer classification while real-time diagnostic help is provided to healthcare professionals.Developing the whole application using Python has the benefit of cohesiveness in all the layers of the system, hence enhancing maintainability and the smoothness of development.

IV. Hybrid AI Models in Preprocessing:

Along with the preprocessing methods offered with state-of- the-art techniques, python based system uses hybrid AI models to identify and classify cervical cancer. This preprocessing pipeline integrates all the following:

- Normalization: This technique standardizes pixel inten- sity between images. Resizing and Rotation: Resizes images to a uniform size and orientation, thus preparing them for feature extraction.
- Contrast Enhancements: Enhances critical details in cer- vical images, allowing the AI models to identify abnor- malities with higher accuracy.
- ShuffleNetV2-LightGBM: ShuffleNetV2 is a lightweight CNN for efficient feature extraction. It reduces com- putational complexity while maintaining high accuracy, making it suitable for real-time applications.
- LightGBM: is a gradient-boosted decision tree algorithm for the rigid classification of the extracted features. It will strike a balance between fastness and accuracy, which has enabled healthcare providers to process huge images quickly.
- InceptionV3-XGBoost: InceptionV3 resorts to deep fea- ture representation algorithms that can extract complex patterns in cervical cell images. The multi-scale feature extraction method of InceptionV3 makes it sensitive and specific for cervical cancer detection. XGBoost is a strong gradient-boosting algorithm that supports InceptionV3 with fine-tuned classification of cervical abnormalities, reducing false positives and negatives.
- ResNet34-LightGBM ResNet34: Solves the vanishing gradient problem by using residual connections, which enables the model to learn deep feature hierarchies ef- fectively.This is combined with LightGBM to ensure efficient classification even for complex datasets with subtle abnormalities.
- VGG16-LightGBM: An aggregation of VGG16, good for high-level feature extraction abilities, and the Light- GBM model will achieve a strong,

balanced diagnostic capacity. It maintains a balance toward computational efficiency rather than diagnostic power, making its ap- plication feasible with both high-resourced and poor-resourced access.All of these models have been fine-tuned specifically on cervical cancer datasets and are run within the Flask microservice, interacting with the backend to analyze medical images for diagnostic insights stored and visualized on the frontend.

V. Data Management and Security

The system's architecture is devised to maximize its security and data integrity, totally in view of the sensitive character of medical information and the stipulated requirement on health care that includes compliance under HIPAA or Health Insurance Portability and Accountability Act and General Data Protection Regulation or GDPR. Leveraging cutting-edge technologies and security measures, the system guarantees that the data of the patient is secure and accessible only to authorized personnel with optimal efficiency. Below is an exhaustive description of the platform's data management and security aspects.

A. Secure Metadata Storage with MongoDB

The system makes use of MongoDB, a highly scalable and flexible NoSQL database, for storing patient metadata:

1) Scalability: MongoDB has shown to be effective in handling massive, complex data sets, and this is exactly what is needed for managing enormous patient records, metadata for medical images, and AI-generated results. The system scales very easily with the expansion of healthcare institutions, ensuring smooth performance.

2) Efficient Querying: The platform's indexing and query- ing capabilities via MongoDB enable the quick retrieval of patient data, thus reducing delay in the medical decision- making process.

3) Flexible Schema: MongoDB's schema-less structure en- ables the platform to accept new data fields or models easily, thus staying compatible with the ever-evolving AI technologies and diagnostic requirements.

B. Store securely with Amazon S3

All the medical images and videos uploaded into the system are stored securely using Amazon S3:

- Encryption at Rest: Amazon S3 by default uses Server- Side Encryption, encrypting all files media and it is stored with keys managed by AWS.This is enhancing protection against unauthorized access.
- Encryption in Transit: Data uploaded to or retrieved from Amazon S3 is encrypted with the TLS/SSL protocol over the transmission channel so that interception or tampering cannot occur in the data transfer.Redundancy and Durability, Amazon S3 automatically tiers data across multiple availability zones that ensure a high level of data availability and prevents data loss in the event of failure or disaster of the hardware.

C. Role-Based Access Control (RBAC)

The role based access control system limits the sensitive data and functionality access to a user depending on the roles installed. Access Levels Only those healthcare providers, including doctors and specialists, are allowed access to specific

patient data, or they can start the AI processes, or can see the AI-processed results. More access for role management and system operation exists for administrative users.

- Audit Trails: All user actions are logged in comprehen- sive audit trails, which track access to patient data and platform functionality. This supports accountability and assists in identifying unauthorized attempts.
- Session Management: The safe management of sessions will automatically log the user out after a series of inactivity periods.This reduces the threat of any misuse through idle sessions.

D. End-to-End Data Encryption

The software uses advanced encryption techniques to secure patient data moving across the network and when placed at rest:

- Encryption in Transit: All messages that travel from the frontend to the backend and between the Flask microser- vices are encrypted with TLS/SSL. This would prevent any capture of patient information and medical images during the transmission process.
- Encryption at Rest: Patient metadata in MongoDB and media files in Amazon S3 are encrypted with AES- 256 encryption, one of the most recognized and secure encryption standards around the globe. Amazon KMS will therefore securely manage all encryption keys. It can automatically rotate them and provide better mechanisms for access control for security purposes.

E. Secure API Access and Communication

The system has strict APIs access controls that will prevent illegal access or data leakages.

- Token-Based Authentication: APIs are protected using JSON Web Tokens (JWTs) issued after authenticating the user. Each API request is validated against these tokens, so only authorized requests are processed.
- CORS: The platform is very strict about its CORS policy, allowing requests only from trusted domains, thereby minimizing the risk of XSS and other malicious attempts.
- Rate Limiting: To prevent brute-force attacks or high- volume requests, rate limiting has been used for all the API endpoints; this limits how many requests a user can make within a timeframe.

F. Health care regulation compliance

The system is entirely compliant with healthcare regula- tions; thus, it satisfies all the legal requirements put in place for dealing with sensitive medical data.

- HIPAA Compliance: It is absolutely compliant with all the stringent regulations of HIPAA to ensure data confi- dentiality, integrity, and availability. It's GDPR compliant and ensures legally transparent processing for the users under the jurisdiction of GDPR, which is inline with data anonymization, requesting user consent, and the right to access or delete according to regulation under GDPR.

- Data Minimization: Only what is necessary for the func- tionality of the platform is collected and stored by the system. Once AI processing is done, the temporary files created in processing are automatically deleted, thus con- trolling the exposure risk. Continual and Live Monitoring with Threat Detection Advanced monitoring mechanisms ensure that the system's integrity continues to be strong and will consequently detect security threats soonest.
- Real Time Monitoring: Continuously keeps its eyes open towards the all such sensitive operations done with it for logins or even for uploads. All multiple log in failures and malicious APIs calls directly gets alert through further investigation processes.
- Log Management: All activities will be logged and stored securely thus allowing thorough auditing and trou- bleshooting. This will, therefore, give full traceability of operations carried out on the platform.
- Automated Alerts: The system automatically sends alerts for events critical in nature, such as failed encryption attempts or unauthorized access to data, so system ad- ministrators can intervene without delay.

G. Future Security Improvements

To always be at its best security state, the system is under constant development with improvements planned:

- Zero Trust Architecture: The solution will implement a Zero Trust security model, whereby each user and device request is verified and authorized, regardless of location or access history.
- Explainable AI Security: The deployment of explainable AI models ensures that all AI-based medical predictions will be transparent and in line with ethical standards and principles, so the healthcare providers understand each result.
- Distributed Storage Encryption: The System is Planning to use distributed key management systems in order to give efficient protection even for large datasets, reducing the threat further against stored medical data.

VI. Results

The experimental evaluation of our Python-based cervical cancer classification platform assessed four deep learning architectures with gradient boosting classifiers using precision, recall, F1-score, and accuracy across five cervical cell classes (dyk, Koc, Mep, Pab, and Sfi), as shown in I and 2. The classification results, as seen in 3, indicated that all architec- tures performed consistently at a high level. The ResNet34- LightGBM and ShuffleNetv2-LightGBM achieved the highest accuracy at 99%, while Inceptionv3-XGBoost and VGG-16-LightGBM were 98ResNet34-LightGBM had the best perfor- mance, exhibiting 100% precision for all classes of dyk, Koc, and Pab, as well as 99–100% F1-scores with an ability to classify perfectly the Pab class. ShuffleNetv2-LightGBM was equal in performance, and 100% for Pab was achieved with a slight decline in Koc recall to 97%. Inceptionv3-XGBoost performed between 97% and 99% precision, and it was bestin the Pab and Sfi classes with 99%, while Mep had 97% precisions.VGG-16-LightGBM achieved 98% accuracy, and perfect classification was obtained for Pab, but slight variation in Mep precision was 96% and recall was 98%. Across models, the Pab class was uniformly optimal for classification, and the Koc class had a bit lower recall of 96%–99%. ResNet34- LightGBM maintained the most balanced relationship between precision and recall, and all models achieved very high pre- cision (≥ 96%) and recall (≥ 96%). Even though ResNet34- LightGBM was able to outperform ShuffleNetv2-LightGBM marginally in general, all networks performed significantly well for the task of cervical cancer classification. These results confirm the strength of our Python-based classification platform as all architectures proved to be powerful in cervical cancer classification. ResNet34-LightGBM and ShuffleNetv2- LightGBM had marginally better results, but all models were highly accurate and thus potentially applicable for practical use in automated diagnostic workflows.

RESULT COMPARISON TABLE					
Model	**Classes**	**Precision**	**Recall**	**F1 Score**	**Accuracy**
ShuffleNetv2-LightGBM	dyk	99%	99%	99%	99%
	Koe	99%	97%	98%	
	Mep	99%	99%	99%	
	Pab	100%	100%	100%	
	Sfi	98%	99%	98%	
Inceptionv3-xgboost	dyk	97%	98%	97%	98%
	Koe	98%	96%	97%	
	Mep	97%	97%	97%	
	Pab	99%	99%	99%	
	Sfi	99%	99%	99%	
Resnet34-LightGBM	dyk	100%	99%	100%	99%
	Koe	100%	99%	99%	
	Mep	99%	99%	99%	
	Pab	100%	100%	100%	
	Sfi	98%	100%	100%	
VGG-16-LightGBM	dyk	99%	99%	99%	98%
	Koe	98%	97%	97%	
	Mep	98%	99%	98%	
	Pab	100%	100%	100%	
	Sfi	98%	99%	98%	

TABLE I
RESULT COMPARISON OF DIFFERENT MODELS

Fig. 2. Overall model accuracy comparison

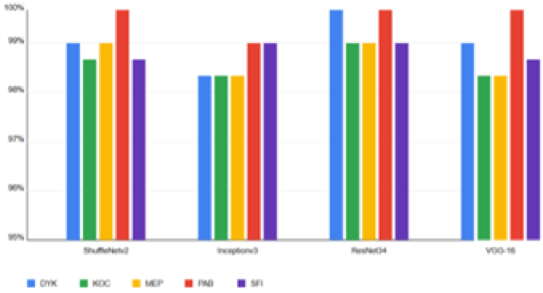
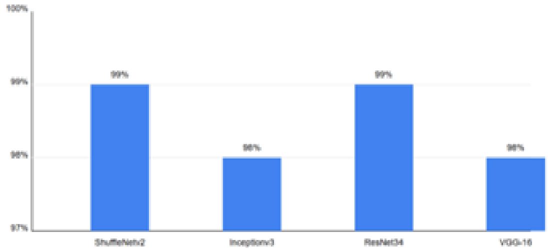


Fig. 3. Model Performance across Cell classes (F1- Score)

Figure Labels: Use 8 point Times New Roman for Figure labels. Use words rather than symbols or abbreviations when writing Figure axis labels to avoid confusing the reader. As an example, write the quantity “Magnetization”, or “Magnetiza- tion, M”, not just “M”. If including units in the label, present them within parentheses. Do not label axes only with units. In the example, write “Magnetization (A/m)” or “Magnetization {A[m(1)]}”, not just “A/m”. Do not label axes with a ratio of quantities and units. For example, write “Temperature (K)”, not “Temperature/K”.

VII. Discussion

It integrates the AI model into the central framework of cervical cancer imaging, making a now major limitation in the traditional diagnosis of cervical cancer. It improves diagnostic accuracy since the interpretive subjectivity and variability by hybrid AI models decrease the uncertainty of image interpretation. Its sensitivity and specificity increase this possibility toward health care professionals gaining better probabilities for clinical decision-making. In addition, the cen- tral approach towards data management optimizes workflow efficiency for seamless access of medical imaging data in compliance with highly set standards for healthcare security. Although such advancements have been made, there remain some unsolved challenges. First and foremost, larger and more diverse datasets are needed to enhance the generalizability and robustness of AI models across a variety of subtypes of cervical cancer. The expansion of the dataset in order to be representative of a large number of cases from different demographic groups and through varying imaging conditions will improve adaptability of AI models, thereby making them more effective in real-world clinical settings. Real clinical validation of results produced by AI is also an immense requirement for its performance in every clinical diagnostic scenario. Testing on a large-scale basis using retrospective and prospective clinical data will be required to build trust and eventually regulatory sanction. Future work would be on enhancing the dataset and further addition of diagnostic modalities, such as colposcopic imaging, for further improve- ment of diagnosis accuracy. The system will add a dimension to diagnosis by providing a



much-needed integration of AI- driven colposcopic analysis with cervical cancer screening. This would then help to add cytological analysis and real-time visual assessment, leading to a very high increase in early detection rates and hence the patient’s outcomes. Finally, integration of explainable AI techniques, which could make AI-based diagnoses more understandable and interpretable to health professionals, is an aspect that needs much improve- ment. With explainable AI, it becomes possible to describe how and why the AI models arrive at their conclusions, so that trust and support in clinician evidence-based decision- making could be developed. This is most important in medical imaging, wherein clear justifications for diagnoses would be necessary in treatment planning. Scaling up to support large institutions like health care, the system will also look into distributed processing in the cloud for its large-sized medical images for computation, enhancing scalability and reducing latency. Distributed cloud architectures are designed to give ultimate scalability and increased processing speeds for the system to still be responsive even at peak usage times. Imple- menting dge omputing solutions can also enable certain AI computations to be performed closer to the source of the data, reducing dependence on centralized cloud servers and enhanc- ing real-time processing capabilities. The developed Python- based AI system marks a turning point in diagnostic imaging, showing how, with such a system, workflows in diagnosis may become optimized and more efficient, the precision of the analysis being enhanced.The system gives more time to healthcare professionals with patients while ensuring the use of AI-driven insights to further enhance diagnostic confidence, with the reduced need for manual interpretation. The system will continue to evolve in order to meet the current challenges, hence staying ahead in the curve of AI-powered healthcare innovation.

VIII. Conclusion

The system represents the possibility of integrating AI- driven diagnostic tools with centralized imaging frameworks to transform cervical cancer screening and diagnostics. The use of hybrid AI models along with secure data management practices and user-friendly interfaces makes it possible to provide a scalable and efficient solution for the challenges faced in traditional medical imaging workflows. These findings show the effectiveness of the system in increasing the rate of early detection, improvement in diagnostic precision, and reducing workflow, primarily in resource-scarce regions where the disease burden is significant. Future work will include building on datasets and integrating other types of diagnostic approaches as well as distributed processing for better per- formance and scalability of the platform. It establishes itself as a key innovation in modern health diagnostics through an innovative approach.

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