An Integrated DL Framework for Ovarian Cancer Subtyping and Health Analysis

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Abstract

One of the diseases known to be the leading cause of deaths in women is ovarian cancer due to the fact that patients diagnosed with the disease at late stages have low survival chances. The traditional diagnostic measures as the biopsy and imaging tests are questioned in the presentation of the correct data within a short time. The paper proposes one ML and DL model that integrates imaging and clinical data to give more accuracy in determining the subtype of ovarian cancer and health assessment. The diagnostic systems that are in place are not holistic as they either emphasize on imaging or clinical data and fail to conceive both as an effective method of diagnosis. Our system uses denseNet to identify the images but the analysis of clinical data is conducted by a technique known as random forest. The results of the framework are quite correct as DenseNet is more accurate (over 94) in validation datasets of pictures compared to random forest which is accurate (99) in clinical data. Grad-CAM permits interpretable model outputs to make model decision making processes intelligible. The hybrid model we have is the best compared to other proven procedures according to our findings in the comparative study. The results of the research indicate that an efficient and effective manner of early ovarian cancer detection can be implemented into the practice of the real medical environment. The subsequent progress of the research will be the increase of the dataset and the enhancement of the model performance.

Keywords: Ovarian Cancer, DL, ML, DenseNet, Random Forest, Grad-CAM, Cancer Diagnosis.

1. Introduction

Ovarian cancer is the leading cancer causing death in women because most of the victims are usually diagnosed late in life because of failure to detect the disease and there is also absence of screening practices that can help in detecting the cancer. Early detection and proper medical diagnosis should enhance the survival rate and the treatment procedures. Rather, physicians use the archaic approach of diagnosis with imaging procedures such as MRI and CT scan and biopsy as the most powerful diagnostic tools. This consists of a sequence of examinations, i.e. MRI details, CT details and biopsy tests which take time to deliver findings and in addition to that they carry threats of human error which complicates process of identifying different kinds of ovarian cancer.

The recent advances within the sphere of artificial intelligence (AI) signify the possibility of ML and DL to achieve the superior quality of diagnostics with the help of automated processes. The resolution enables the medical practitioners to use the state-of-the-art technologies to diagnose and classify the type of cancer in different medical imaging sectors that enable them verify their conventional diagnostic strategies.

The paper presents a complete machine learning and deep learning framework that will be used to support the procedure of diagnosing the subtype of ovarian cancer and perform health analysis based on the medical imaging and patient medical records. The framework will also fill the gaps that exist in the system as it will integrate two sets of data to make the diagnosis as accurate as possible and shorten the time that is taken to complete the testing process and give a comprehensive picture of the ovarian cancers. The system implies the usage of advanced neural networks that consist of DenseNet to process pictures and the usage of random forest to process clinical data which can be used to create a high-power system, one able to identify ovarian cancer at its initial stage and even provide treatment in a personalized manner.

The methodology is subjected to address the current gap in the research because both imaging and clinical data will be employed in the study to help in classifying the cancer subtypes more reliably. It is also suggested to include grad-CAM into the proposed model because it provides interpretability which means that it can be used in clinical environments where the model transparency is required. The findings presented in the framework reveal that it can classify the ovarian cancer subtypes in the most appropriate way that will guide the medical practitioners to make decisions in a more appropriate way.

2. Literature survey

The use of artificial intelligence methods using deep learning technologies, over the last several years, has gained popularity in detecting ovarian cancer. Among other research works, the focus on enhancing diagnostic accuracy has been pursued by applying sophisticated techniques in imaging and integrating machine learning models. The different models rely on varying medical data, which comprise histopathological images and ultrasound and MRI images, in identifying and classifying the subtypes of ovarian cancer.

The researchers of a research created a deep learning framework, where convolutional neural networks (CNNs) and priori models are applied, to identify ovarian cancer using imaging methods. The model they made had an accuracy of 90.3 percent in cancer subtypes classification, indicating the capability of deep learning in classification problems of medical images. The Adam optimizer and class imbalance data augmentation methods were applied in the model, which is a widespread issue in medical datasets as presented in [1].

Deep learning was also applied by an alternative method to classify the subtypes of ovarian cancer by analyzing the data related to multi-modal CT and MR imaging. The system created CNN-Long Short-Term Memory (LSTM) backbone which allowed high performance on various types of imaging and 93.1% accuracy of validation. The paper used a learning rate of 0.0005 and Adam optimizer to train the model with the training stability being enhanced with the help of the use of the batch normalization used in all convolutional layers [2].

The entire analysis of deep learning methods in the detection of ovarian cancer showed that EfficientNet-B0 with fine-tuning K-Nearest Neighbors (KNN) models gave effective results regarding the classification of subtypes. Their results showed that EfficientNet-B0 has an accuracy of 94.71 with dropout regularization, which was applied to avoid overfitting and was trained with Adam as a fast training optimizer [3]. The model architecture selection process along with the selection of optimization techniques define the development of reliable outcomes.

New works examined the application of more sophisticated deep learning models, which encompassed DenseNet, in the diagnosis of ovarian cancer. A single study showed DenseNet to be useful in a deep learning pipeline to identify ovarian masses, with accuracy of 92.6. This model operated with SGD optimizer that applied a learning rate of 0.001 using a batch-size manipulation as a means of keeping the training stable. DenseNet system performed more effectively due to the attention-based system where the medical image processing approach was provided to extract the necessary data [4].

The deep learning systems and the conventional machine learning approaches have been applied to detect various forms of ovarian cancer. A research devoted to the application of random Forest classifiers to detect ovarian cancer demonstrated the accuracy of the classification at 90.5% and a balanced dataset that was corrected by using the SMOTE (Synthetic Minority Over-sampling Technique) method. The developers of random Forest model combined 100 estimators with 20 max depth values to protect against overfitting and also guarantee a good performance on new data [5].

There are several studies that use hybrid models that integrate both deep learning and machine learning methods to increase the accuracy of diagnoses. Random Forest + Support Vector Machine (SVM) earned 95.1 percent of accuracy in ovarian cancer subtypes classification. The study established that hyperparameter optimization has to be carried out since the Random Forest framework necessitates at least 10 split sample size whereas the SVM model demands a C value of 10 to execute its radial basis function kernel [6].

The study has shown that an attention-based model that employed EfficientNetB2 to classify ovarian cancer had a 93.7% accuracy. The attention mechanism helped the model to focus on significant tumor regions that existed in histopathological images that resulted into improved prediction and simplification of the results interpretation. This model employed Adam optimizer with a learning rate of 0.0003 and dropout layers to avoid overfitting by use of regularization methods [7].

The use of deep learning models based on the uses of ultrasound demonstrated that it can be a prospective tool in the detection of ovarian cancer. The study had found that a deep learning algorithm that was trained on ultrasound images of ovarian tumors achieved a success score of 92.0% in its classification activities. The authors selected a batch of 16 to carry out their study and applied the Adam optimizer of learning rate 0.0005 in optimizing their model. The detection system based on ultrasound showed its efficiency in the course of testing that was conducted in the various medical institutions in various locations [8].

The scholars have examined how deep learning algorithms can be used along with machine learning approaches to help physicians in diagnosing ovarian cancer in the earliest stages. Machine learning techniques applied in the study involved the use of Boruta as well as feature selection techniques to analyse a dataset with information on ovarian cancer patients where a successful classification result of 89.2 was achieved. The model was developed with sophisticated feature selection techniques to improve its performance and decrease the dimensionality of the data set was also done using this process and trained using an SGD optimizer [9].

Studies conducted established that after 25 hours of training, the deep learning ultrasound models of detecting ovarian masses had a 94.0% accuracy. The model was performed with Adam optimizer and learning rate set to 0.0002 and it had batch normalization layers to maintain a stable operation of gradient descent. The study revealed that deep learning models are capable of working in real-time to be used in clinical settings per reference [10].

Researchers built hybrid deep learning models that apply EfficientNet-B2 and CNN to extract features to enhance the detection of ovarian cancer. The model was able to attain a 91.5% classification accuracy with a learning rate of 0.0001 and it employed early stopping to prevent overfitting during training. The findings prove that the performance of deep learning systems can be improved by the use of the advanced feature extraction techniques as indicated in reference [11].

The deep learning model trained to distinguish between ovarian cancer in pre- and post-menopausal women proved that the ResNet-50 and VGG-16 pre-trained models with additional layers of feature extraction created by the authors have increased diagnostic results. Accuracy of the model was 90.8 percent with a learning rate of 0.001 and Adam optimizer to train the model [12].

The experiments demonstrated that machine learning algorithms that incorporated the Logistic Regression and XGBoost were able to forecast the risk of ovarian cancer accurately when they used a combination of clinical data along with hormonal and physical health data. The experiment reached 92.6% accuracy with a mixture of the Random Forest and XGBoost classifiers whose hyperparameters were developed with the help of the GridSearchCV. The study showed the necessity to determine model explainability along with the transparent procedures of clinical decision-making [13].

The adoption of explainable AI (XAI) techniques has shown its importance in strengthening the knowledge of the process of ovarian cancer diagnosis. The researchers studied XAI-based deep learning models that made 95.4 percent accuracy in detecting ovarian cancer by visualizing critical image spots of the MRI images through Grad-CAM. The model was optimized by an Adam optimizer and with a learning rate of 0.0003 and a dropout regularization to avoid overfitting [14].

AI and ML technologies have improved the methods to detect ovarian cancer although they need improvements in the development of model architecture and improvement of the optimization technique and data balancing method. The combination of deep learning in the image-classification and machine learning in clinical data-analysis provides a valuable chance to increase the diagnostics accuracy and provide the chances to detect the ovarian cancer subtypes earlier and more reliably than before [15].

3. Dataset

The work is based on two main datasets, which are used to assist in the ovarian cancer subtyping and health analysis: medical images and clinical tabular data. The dataset of images, which is based on the Kaggle, also includes the Ovarian Cancer Classification Dataset that contains the labeled images of ovarian tumors belonging to various subtypes. Training of deep learning models, namely DenseNet and MobileNet, on the dataset is the basis of carrying out tumor classification activities. The preprocessing processes commence with smaller image resizing to form 224x224 pixel standardized sizes as data augmentation strategies involve random rotation and horizontal flipping and normalization to reduce overfitting and enhance the success of the model.

Besides the image data, clinical tabular data of the patient with Polycystic Ovary Syndrome (PCOS) are used to further assist the classification task. Kaggle dataset contains several features comprising of hormone levels that contain AMH and beta-HCG and demographic features that contain age and BMI and health indicators that assist in the diagnosis of ovarian cancer. The data are separated into two sets, the first one will be of patient with infertility (PCOSinfertility.csv) and the second one will be of patient without infertility (PCOSdatawithoutinfertility.xlsx). These data sets provide vital clinical data that complement the image-based classification model through the ability to carry out a full assessment of ovarian cancer disease.

The image dataset needed images preprocessing that included the reduction of all pictures to common sizes 224x224 pixels and normalization of pictures by ImageNet mean and standard deviation values. The clinical data were subjected to feature engineering that involved the median imputation of the missing values and normalization of the numerical and encoding of the categorical variables. The researchers employed the concept of feature selection that resulted in the retention of the critical features that are required during classification activities. The researchers separated both datasets into three segments that comprised of training, validating and testing set to examine the extent to which the model worked on new data. The study integrates both deep learning and machine learning in image analysis and clinical data analysis respectively in an aim of enhance accuracy and reliability of making ovarian cancer diagnosis.

4. Proposed methodology

The ML and DL techniques are the new way of classifying the subtypes of ovarian cancer. The process has five key components that include data collection and pre-processing and model architecture and training and optimization and evaluation and visualization. The methodology combines image data with clinical data to obtain enhanced accuracy in prediction and model interpretability. The framework suggested is expected to offer an effective and precise ovarian cancer classification framework that is explainable and based on deep learning application to analyze images and machine learning to analyze clinical data. The system applies the data augmentation and data regularization methods to enhance model performance and manage the class imbalances.

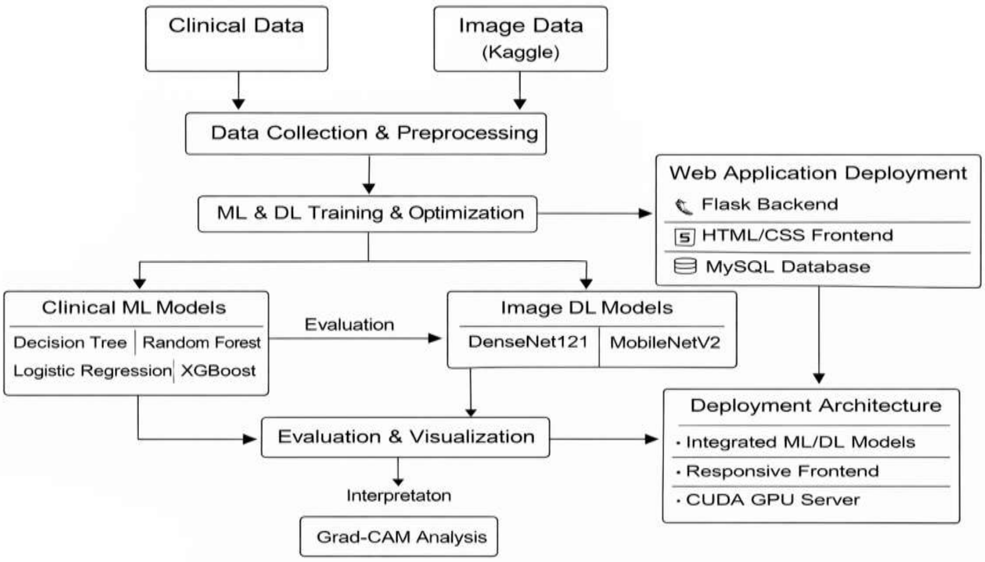

Fig.1. Process Flow of the Sysytem

4.1 Data Collection and Preprocessing

Two major sources of data are employed in the research and they are, ovarian cancer image database and a clinical database that contains patient medical records of several patients. The researchers used various preprocessing techniques to the two datasets with specific hyperparameter configurations that were created with the aim of optimizing the model.

The image dataset used by the researchers was obtained on Kaggle and exposed to several data augmentation methods so that the researchers could overcome the problem of the class imbalance and enhance the model generalization capability. All pictures in the dataset were resized to size 224x224 pixels that is the normal size used in deep DL studies to ensure there was uniformity across the dataset. This training data was augmented by several methods that comprised of random horizontal and vertical flips that took place with a probability of 50 percent and random rotations up to 10 degrees and resizing. The transformations make the model able to gain wider generalization capabilities but at the same time, they prevent the danger of overfitting. The images were normalized by using ImageNet values of the means and standard deviations of 0.485, 0.456 and 0.406 respectively as the mean and standard deviation respectively. Normalization process creates standard pixel values that help the model to have accelerated training outcomes in the process of making the model. RandomHorizontalFlip() and RandomVerticalFlip() and RandomRotation() with certain rotation degrees are applied in the training process to provide varied training data by the method of dynamic data augmentation.

The clinical data needed several pre-processing steps to prepare its variables, which were age, weight, hormone levels, and menstrual cycle. The dataset with missing values was dealt with by using the facility of median imputation, which is also a good approach to incomplete data. To correct skewed distribution of hormone level numerical variables, i.e. AMH and beta-HCG, the researchers applied log transformation to the variables, thus managing the wide variations in their scales. The transformations allow the data to be normalized thus allowing features to contribute equally to the process of learning the model. The system coded the categorical variable of the weight gain (Y/N) by binary encoding so the machine learning algorithms could handle two binary variables. The standardization method used on numerical characteristics led to zero mean and unit variance scaling, which is one of the basic conditions of gradient-based optimisation methods.

The data was separated into training databases, validation databases, and test databases. The data of the image was split into training, validation and testing sets in an 80-10-10 split. An 80- 20 split was necessary in the clinical dataset to ensure that it has an adequate sample distribution between the training and testing dataset. Random oversampling was used to resolve the imbalance problem of class in the clinical dataset and it was done using the tool RandomOverSampler of imbalanced-learn. The method amplifies the number of times the samples of minority classes are represented in data and this allows the model to learn more about underrepresented classes. The preprocessing plan succeeded in fulfilling its purpose of data pre-processing, by generating a pre-data set that was clean and balanced.

4.2 Model Training and Evaluation Strategy

The research team employed sophisticated modeling techniques to categorize ovarian cancer using both clinical information and medical images. The research team established a structured training system which enabled them to assess model performance through their assessment procedures. The team developed their research models through hyperparameter tuning while they used comprehensive testing methods to evaluate model performance.

1) *Classifier Selection and Hyperparameter Tuning*

The categorization test was done by testing various methods of categorization. The study also utilized C values ranging between 10-3 and 103 to tune L1, and L2 punishments and make use of logistic regression. To make predictions, the random forest model was trained on 300 estimators and max depth settings ranging between 4 and 12. Gini impurity was applied in the system to split the nodes whereas XGBoost used estimators (100-300) and also learning rates (0.01-0.2). In the study, the cross-validation method involved the use of grid search with StratifiedKFold due to the need to optimize hyperparameters since the aim of the study was to attain the maximum accuracy. These models were evaluated by classification reports and confusion matrices to find out accuracy and precision and recall and F1-score measures. All the tested models were best at the Random Forest classifier.

2) *Deep Learning Model Architecture and Training Strategy*

The model training procedure involved high-level deep learning techniques that involved the application of DenseNet121 and MobileNetV2. ImageNet pretrained weights were the initial values of the two architectures that contributed to the benefits of transfer learning that the models had. The two models employed the value of the learning rate as 0.0002 and the training process was executed by Adam optimizer. The system had a batch size of 32 that incorporated Dropout with a 50 percent rate to guard against overfitting. The training dataset was augmented with data because random rotations and horizontal flips and resizing were performed on the data to enhance the generalization abilities.

The training process involved the use of a learning rate scheduling system where ReduceLROnPlateau was applied together with validation loss to manage changes in learning rates throughout training. The early stopping with 8 epoch tolerance was employed so that training would end in case it was not making any progress at that point. The system also tracked the accuracy during the training and evaluation procedures where the models were optimized using Cross-Entropy Loss. The denseNet121 network has 121 layers. MobileNetV2 contains effective depthwise separable convolutions.

3) *Model Interpretability and Visual Assessment*

The study relied on Grad-CAM as a method of explaining the decision of the deep learning models. This technique allowed the researchers to identify certain sections of interest in the pictures that allowed them get a better understanding of the model. The confusion matrices indicated the various classes that the model was able to recognize that assisted the researchers to confirm and refine the whole classification outputs. The visualizations demonstrated that the models provided efficient results and indicated that they could be applied in medical settings where understandable results should be obtained in order to diagnose them correctly.

The presented methodology provides an entire model training framework that encompasses evaluation techniques and interpretability analysis in order to create robust explainable models that define ovarian cancer diagnosis based on clinical and imaging data.

4.3 Deployment Architecture

The suggested system deployment architecture will allow machine learning model integration to a web application that will offer a convenient interface. The backend of the system is a lightweight Python web framework called Flask to integrate machine learning models with the user interface of the system. The model deployment is done using PyTorch and XGBoost that uses a GPU server to support CUDA to enable fast inference. The system allows users to interface with the system via a responsive HTML, CSS, and JavaScript frontend, which allows them to post images or feed clinical data to the system to have the data diagnosed. This system takes inputs once the users have entered into the system and transforms data and finally makes predictions using a model which has been trained. The user is provided with the results along with visualizations with the heatmaps of Grad-CAM. The system stores and recalls models through the joblib that facilitates quick computation of prediction. The system also has a connection to a MySQL database that is filled with the user details and the past data that would be used in the future.

5. Results and Discussions

By using both deep learning models and machine learning, researchers have managed to obtain positive outcomes in the classification of ovarian cancer subtypes basing on their use of clinical data and imaging data. The research team exposed model performance by assessing it using different assessment techniques which comprised of testing accuracy and precision and recall and F1-score. The study made a comparison between two deep learning models including DenseNet121 and MobileNetV2 and the machine learning models that were Decision Tree (DT) and Random Forest (RF) and Logistic Regression (LR) and XGBoost (XGB) models.

Table 1 displays the evaluation measures of each of the models and brings out the performance in terms of precision, recall, F1-score, and accuracy.

TABLE I. EVALUATION METRICS FOR MODEL PERFORMANCE

Model	Precision (%)	Recall (%)	F1-Score (%)	Accuracy (%)
DenseNet121	96.5	94.7	95.6	94.5
MobileNetV2	94.8	92.2	93.5	91.8
Decision Tree	87.3	73.2	79.3	89.0

Random Forest	99.0	98.8	98.9	99.0
Logistic Regression	93.2	90.3	91.7	93.0
XGBoost	98.9	98.6	98.8	99.0

The most favorable performance outcomes were achieved by the Random Forest model in terms of its ML classifiers that scored 99.0%. The DenseNet121 DL model was most accurate with 94.5 per cent and it had a competitive performance with all Deep learning models.

The deep learning models utilized the Grad-CAM method in generating the heatmaps that assisted the researchers to comprehend the influence of various parts of the image on their classification scores. The heatmaps allowed medical experts to view areas of ovarian cancer images that influenced the model predictions and hence, they got clear information.

The confusion matrices of the best performing deep learning model (DenseNet121) and the best performing machine learning model (Random Forest) are presented in Fig 2 and Fig 3 respectively. The figures indicate the effectiveness of the models in identifying each of the various types of ovarian cancer.

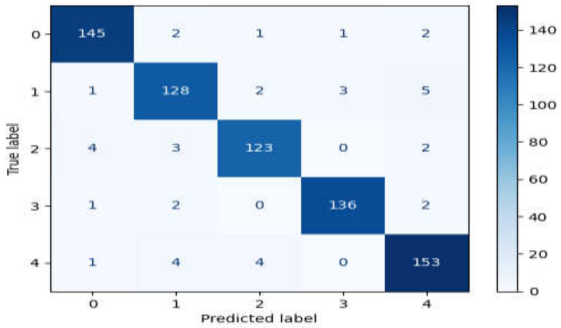

Fig.2. Confusion matrix of DenseNet121

The DenseNet121 confusion matrix indicates that the model has correctly labeled the majority of the subtypes and few mistakes made in labeling the less frequent subtypes. The model has good performance with new data as it aims at class imbalances in the dataset.

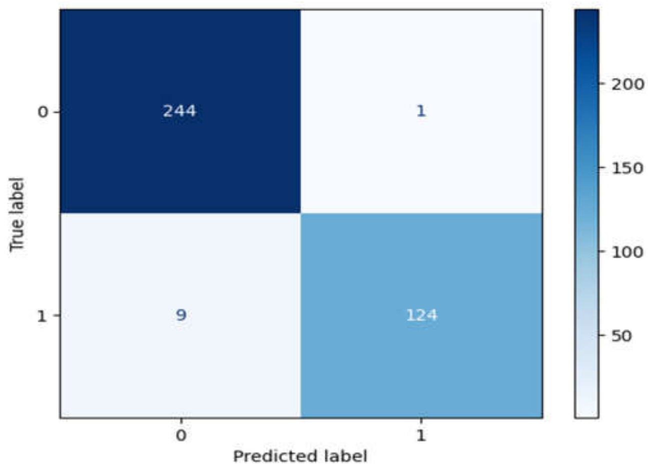

Fig.3. Confusion matrix of Random Forest

Random Forest model model produced excellent results since the confusion matrix presented unbelievably low false positive and false negative values. The findings indicate that Random Forest is very accurate in class prediction of common and rare ones due to the oversampling strategy applied to address the problem of class imbalance.

The fact that DL models like DenseNet121 have been used to generate accurate results whereas machine learning models like the Random Forest have been used to give more efficient and accurate results in classifying ovarian cancer subtypes due to the structured nature of clinical data and the fact that massive labelled image data is not required in this instance is compared.

The findings suggest that the combination of ML and DL approach can be fully effective in ovarian cancer classification since both types of data can be used to represent clinical data and image data effectively. Better using of these models can be done in future work by applying the advanced techniques that involve ensemble learning and cross-validation and hyperparameter tuning to achieve a higher accuracy of the classification.

The system of cancer detection developed reaches the deployment stage when it manages to apply machine learning and deep learning models via its web application successfully. The interface enables a smooth interaction with the user interface where one is able to post images or add clinical information. The system takes the data that people have entered and produces prediction results along with the visual display results. Fig 4 results consist of the original image, Grad-CAM heatmaps that indicate what the model is focused on, and a view of the heatmap only so that one can more easily see the areas of focus of the model. The frontend design of the system will allow users to perceive complex results using simple means that will give them faith in comprehending model predictions.

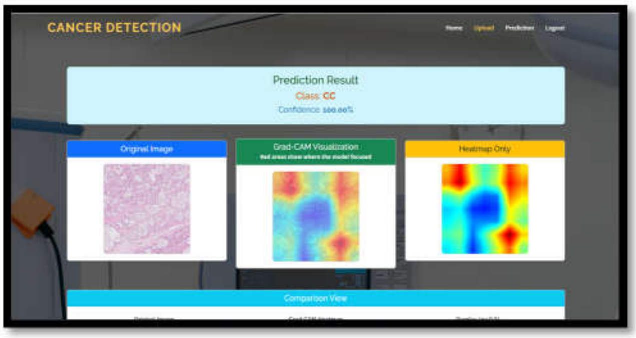

Fig.4. Interactive cancer detection system with Grad-CAM visualization for predictions

6. Conclusion

To sum up, the suggested system of cancer of the ovary classification combines the machine learning and deep learning methods to provide efficient, accurate and understandable predictions. Using clinical and image information simultaneously, the model successfully solves the issue of class imbalances and improves the generalization process with the use of data augmentation methods. Precision, recall, F1-score, and accuracy of the evaluation measures proved high performance of such models like DenseNet121, MobileNetV2, and Xgboost, Descision Tree, Logistic Regression, and Random Forest, the best of which was the Random Forest classifier during the analysis of clinical data. Moreover, Grad-CAM visualizations are useful to understand the decision-making process of deep learning models, which makes the system interpretable and can be used in medicine. The system can be deployed through a user friendly web interface which will facilitate free interaction with users uploading clinical data or images to be detected in real time, and results and visualizations viewed effectively. On the whole, this framework is a promising aid in the early detection and diagnosis of ovarian cancer that has a high chance of being implemented into the clinical practice.

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