

## Review Articles

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# Review on Early Ovarian Carcinoma using Radiomics

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### Abstract:

*Ovarian cancer remains one of the deadliest gynecological malignancies in the world, despite major advances in chemotherapy and surgery. This, according to several research, is related to the considerable heterogeneity in treatment response and prognosis. Mostly, computational approaches for assessing tumour heterogeneity have been developed, which employ medical imaging and radio genomes to look at the whole tumour heterogeneity rather than just a single biopsy sample. This tumoral heterogeneity is not taken into consideration by standard imaging utilising CT or MRI, especially in late stages of peritoneal carcinomatosis. As a result, medical imaging has been recommended as a new field in the assessment of tumour heterogeneity, rather than single biopsy sample, to evaluate the entire tumour burden heterogeneity. In medical imaging there are four basic steps involved for an efficient and accurate detection of ovarian cancer at early stage. This review discusses about the detail evaluation on the various four phases involved in Medical imaging. Thus the review brings out a detail evaluation of Medical imaging undertaken at every stage of processing.*

**Keywords:** Ovarian cancer, Heterogeneity in cancer, MRI/CT Image, Ultrasonography, histopathological images, Bio-markers.

### Introduction:

The yearly incidence of ovarian cancer is estimated to be 204,000 cases worldwide, with 125,000 fatalities. Ovarian cancer is still the deadliest of all gynecologic cancers in affluent nations. More than 70% of women with ovarian cancer are identified with advanced illness, which contributes to the high mortality rate<sup>1</sup>. According to the American Cancer Society, ovarian cancer affects more than 22,000 women each year and is the sixth highest cause of cancer mortality among women. There are no screening tests for ovarian cancer, unlike other gynecologic malignancies<sup>2</sup>. Ovarian cancer is the ninth most frequent malignancy in women and the fifth most common cause of death in women. Undiagnosed ovarian cancer, which can progress from stage 3 to stage 4, is the primary cause of the rising death rate among women<sup>3</sup>. To ameliorate the situation, a lot of work has gone towards early identification of ovarian cancer because early discovery of the disease

leads to a high patient survival rate. Ovarian cancer is hard to detect in its early stages due to its vague symptoms. Women may experience constipation, bloating, early satiety after eating and back pain. While ovarian cancer tends to occur in post-menopausal women, anyone can be at risk. A number of factors, including smoking, endo-me- trioses, polycystic ovary disease, and obesity can raise a woman's risk for the disease<sup>4</sup>. A genetic mutation is responsible for around 20% of all ovarian malignancies. BRCA1 and BRCA 2 are the genes that are most likely to increase the risk of ovarian cancer. Lynch syndrome, a hereditary disease linked to colon cancer, also increases a woman's chances of developing ovarian cancer<sup>5</sup>.

Imaging is important in the early identification of adnexal lesions and is utilized to establish the presence of a mass, identify the organ of origin, describe the tumor's characteristics, and determine the likelihood of malignancy or benignity. Ovarian cancer can be

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discovered by chance using any cross-sectional imaging technique. Ultrasonography (US) is still the first line of defense when it comes to a suspected adnexal mass<sup>6</sup>.

The original image may be processed immediately, without the need for sophisticated image processing. Over the last decade, significant progress has been achieved in the field of digital image processing, particularly for biological image analysis. Histopathology slides may now be easily saved in digitized color picture format because of the availability of contemporary digital scanners<sup>7</sup>. As a result, digital histopathological pictures have become a common data source for computer vision and machine learning algorithms. Several computer-assisted methods are now available to help pathology specialists discover different tissues such as ovarian cancer cells and ovarian reproductive tissues during regular examinations<sup>8</sup>. However, because ovarian tissues vary in form, size, and color, ultrasound scanners that analyze grey scale pictures have a difficult time identifying them. Although time-consuming, tedious, and prone to mistakes, pathological microscopic manual analysis is now regarded as the finest laboratory analysis method for ovarian tissue cells<sup>9</sup>. Screening tests with an electronic device or biopsy test specimens including histopathology digital pictures are required to analyze the ovarian tissues. Ultrasound pictures have a number of disadvantages, including poor visual quality since it analyses grey scale images with low resolution, which means it can only detect big, mature follicles<sup>10</sup>.

Over the last decade, researchers have focused their efforts on improving ovarian cancer outcomes by utilising imaging methods and serum indicators to screen for preclinical, early stage illness<sup>11</sup>. Many biomarkers have shown promise in clinically diagnosed ovarian cancer patients' samples, but some are still overlooked, and marker identification is time-consuming and labor-intensive. The use of imaging techniques such as ultrasound, computed tomography, magnetic resonance imaging, and positron emission tomography (PET-CT) in the diagnosis and localization of ovarian cancers is significant<sup>12</sup>. Machine learning algorithms are used in a CAD-based medical imaging strategy for cancer diagnosis. Feature extraction is a key stage in the machine learning method<sup>13</sup>. Deep learning (DL), a popular artificial intelligence technique, is widely employed in image recognition. Furthermore, the convolutional neural network (CNN) achieves outstanding performance in picture classification preparation<sup>14</sup>.

### **Evolution of ovarian cancer detection process**

Establishing standardized and evidence-based risk assessment algorithms utilising both ultrasound and

MRI has allowed for significant advancements in risk stratification, allowing for reliable definition of adnexal lesions<sup>15</sup>. To distinguish benign from malignant adnexal masses using ultrasonography, the International Ovarian Tumor Analysis (IOTA) group created the simple rules classification system and Assessment of Different Neoplasia in the Adnexa (ADNEX) model<sup>16</sup>. The Society of Radiologists in Ultrasound consensus statement and the Gynecologic Imaging Reporting and Data System, or GI-RADS, are two other ovarian mass characterization and management methods that have been suggested<sup>17</sup>. Most recently, the Ovarian-Adnexal Reporting and Information System (O-RADS), a data system published in 2018, has supplied a standardised lexicon with all relevant descriptors and definitions of the ultrasound's distinctive look ovarian tumours and normal ovaries<sup>18</sup>. As a result, ultrasonography criteria for lesion, verified reporting system. In 2020, management has been planned all-risk categories, as well as their accompanying management techniques, are now included in these recommendations, which were not previously available in any of the preceding versions<sup>19</sup>.

Peritoneal implants have seen less advancements. CT remains the gold standard for preoperative assessment, with implant detection accuracy ranging from 70 to 90 percent<sup>20</sup>. CT, on the other hand, has a low sensitivity (25–50%) for implants smaller than 1 cm, especially in places like the gut surface or mesentery<sup>21</sup>. However, fat suppression, delayed post-contrast imaging, oral contrast agents, and functional imaging such as DWI have allowed MRI detection sensitivities to surpass CT, with DWI's sensitivity and specificity for implant detection reaching 90 percent and 95.5 percent, respectively<sup>22</sup>.

However, any CT or multiparametric MRI examination of peritoneal illness requires a radiologist's subjective interpretation to tell the physician about the volume and placement of the many implants. This method invariably introduces a significant level of variation. Medical imaging has emerged as a novel tool for post processing CT or MR images and creating new quantification measures that relate qualitative and/or quantitative imaging data to clinical outcomes. In contrast to Computer Aided Detection (CAD), which typically involves less than 20 image characteristics, Medical imaging involves hundreds to thousands of imaging features derived from large-scale radiological images<sup>23</sup>. The DCNN architecture is used to create an automated system for predicting ovarian cancer and identifying its subtypes from histopathology pictures. Enhancement, rotation, zooming, and flipping were

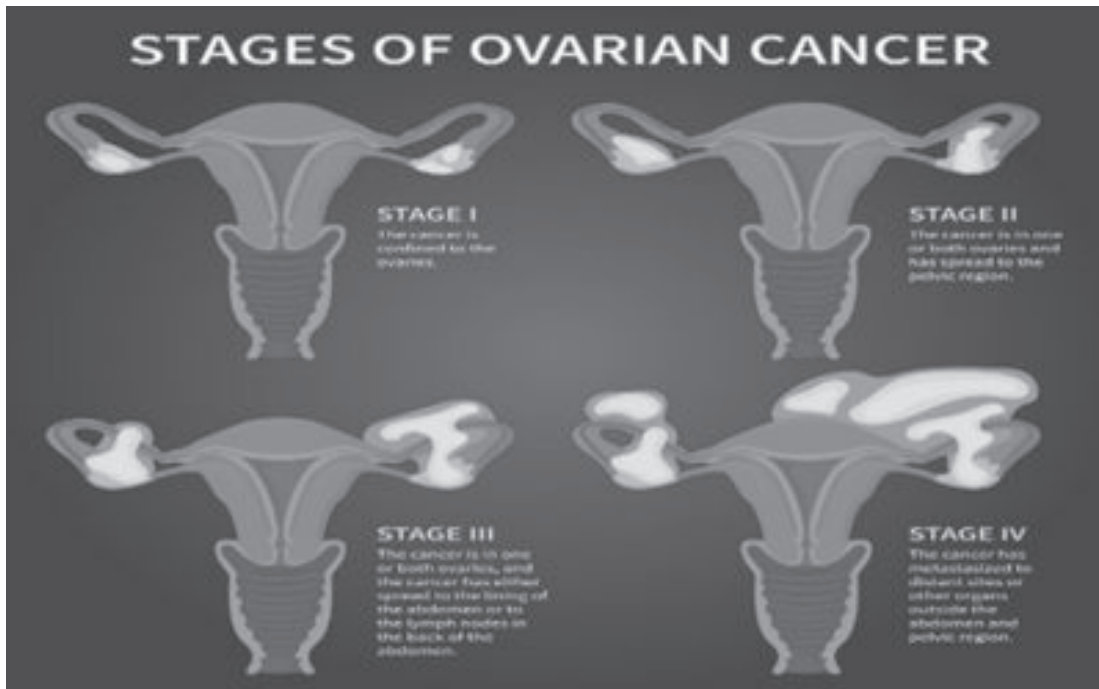


Fig.-1: Four Stage in ovarian cancer

used to improve these photos. The DCNN model predicts and classifies ovarian cancer cells without any prior pathological or biological knowledge<sup>24</sup>.

**Literature Survey Review On Early Detection Of Ovarian Cancer**

A major trend in ovarian cancer prediction has been brought up by medical imaging.

**Various Process involved in imaging**

The following phases are included in the medical imaging analysis process: 1. Pre-processing 2. Segmentation 3. feature extraction and feature selection 4. Classification.

**Pre-Processing Phase**

Before image segmentation, noise reduction is a crucial pre-processing step. The most noise is found in digital

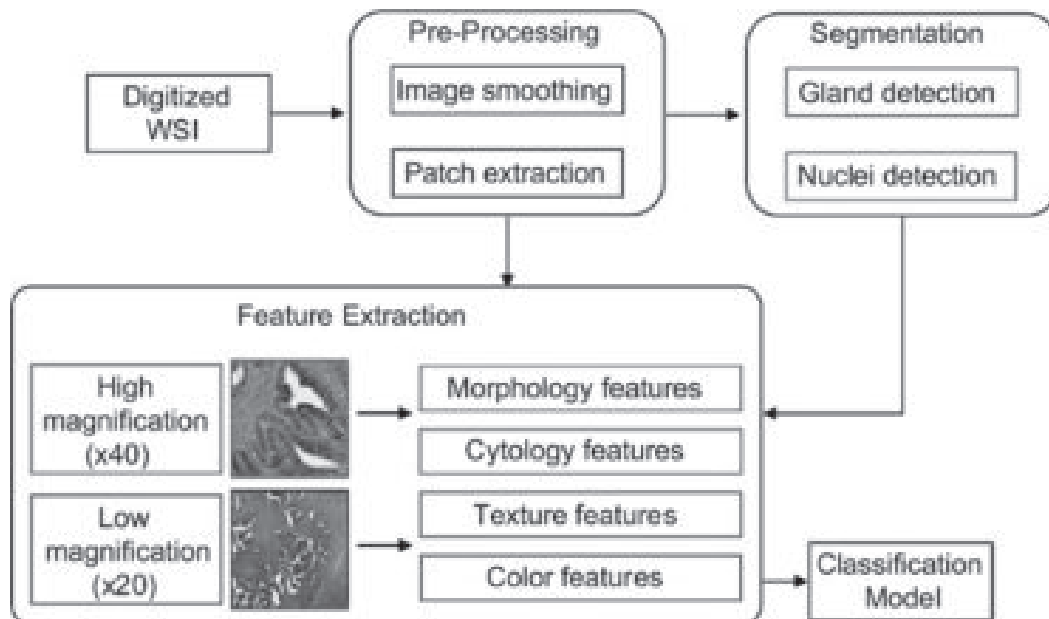


Fig.-2: Flow chart of the Process

pictures of H&E biopsy slides, which show a wide range of intensity. Noisy images are caused by non-uniform illumination that changes contrast<sup>25</sup>. Color balance and homogeneous lighting are two essential factors in digital color imaging. In addition to having balanced colour, an image with uniform illumination provides uniform lighting for all hues around the image.

**Segmentation Phase**

The first step is to get an image. Imaging techniques may be used to analyze any form of medical picture, including X-rays, ultrasounds, CT scans, MRIs, and PET-CT scans. A region of interest or volume of interest containing the allocated area must be established before the characteristics can be computed.

The image is divided into a number of tiny parts using segmentation algorithms. The objective of segmentation is to find the right spots and assess the diagnosis. Unsupervised segmentation is utilised to estimate prognosis and to segment the vascular stained region effectively and correctly. Any of the several methods available for extracting objects from pictures can be used for segmentation. Edge-threshold, and region-based segmentations, as well as clustering algorithms, are some of highly used methods. Because the intensity levels of images in different data sets vary, some of the techniques may be unsuitable for specific images.

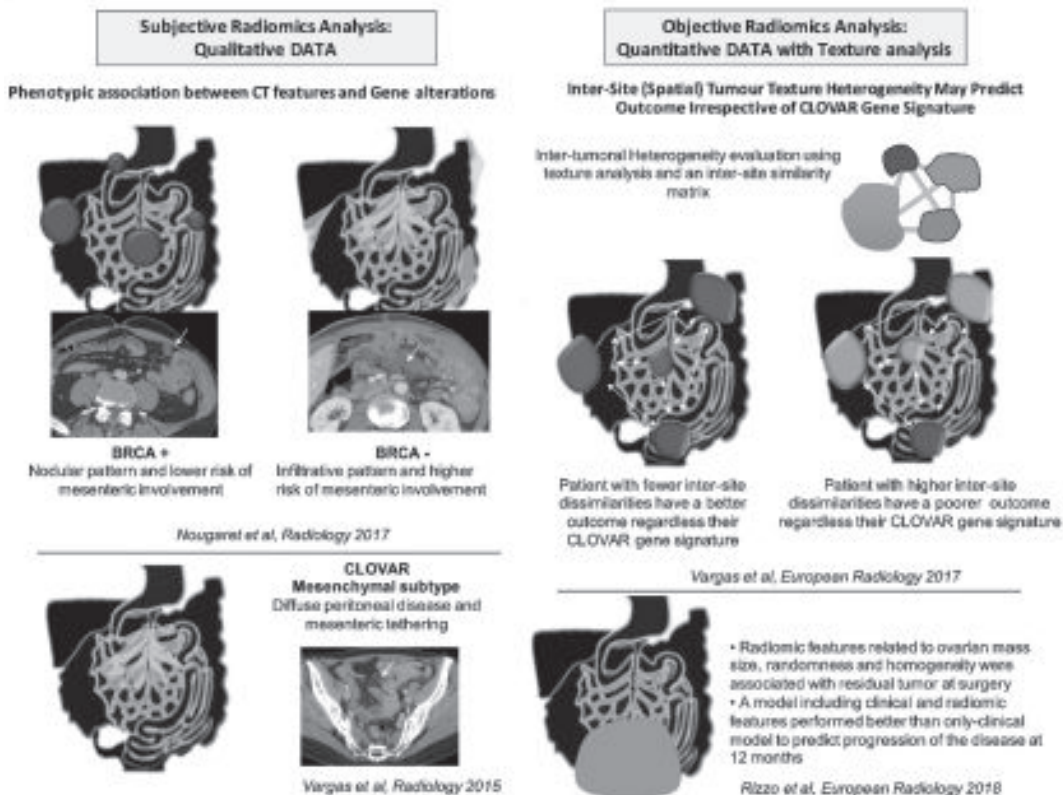
**Feature extraction and selection phase**

The extraction procedure generates a significant number of quantitative imaging measures, which may be divided into following categories:

- First-Order Statistics are histogram characteristics such as energy, entropy, kurtosis, and skewness...
- Shape-based properties including volume, surface area, and sphericity.
- Textural characteristics are included in the following categories, which examine the spatial distribution of pixel intensities:

**Classification**

The objective is to create a mathematical or statistical model that can be linked to a diagnosis, tumour response, or patient outcome. In other words, when given quantitative imaging characteristics, the model is comparable to an algorithm that analyses training data and infers a hypothesis to predict a variable. Algorithms of several kinds have been proposed. Random forest (RF)<sup>26</sup>, least absolute shrinkage and selection operator (LASSO)<sup>27</sup>, artificial neural networks (ANN)<sup>28</sup>, support vector machine (SVM)<sup>29</sup>, and minimum redundancy maximum relevance (mRMR)<sup>30</sup> are among the most prominent algorithms.



**Fig.-3: Alterations that causes Tumor in cells**



The AUC or Harrell concordance index is used to measure discrimination performance. The model's validity may be evaluated both internally and outside. The most popular technique for internal validation is "leave-one-out" cross validation (LOOCV), in which all data is used for training except one data point, which is left out for testing and validation. Another popular approach is the bootstrap, which entails creating a large number of data points (bootstrap sample). Each bootstrap sample represents a patient picked at random, together with the patient's characteristics and result, and the procedure is repeated for the whole cohort of patients<sup>31</sup>.

A screening test for ovarian cancer will need to have a specificity of at least 99.6%. As a result, a screening method for ovarian cancer must have exceptionally high specificity. This is a difficult goal for any technique, which is why tests ultrasonography or several tumour markers must be performed in a sequential order. High sensitivity in samples from people with clinically confirmed condition might lead to erroneous conclusions. The definition of the most appropriate target population for screening is a third difficulty. Postmenopausal status and age (50) are used to establish risk groups for sporadic ovarian cancer, whereas family history criteria and the presence of BRCA1 and BRCA2 mutations are used to identify risk groups for hereditary ovarian cancer. The majority of ovarian cancers are sporadic and affect people of all ages. This four phases are carried out in medical imaging process to accurately detect the cancer lesions and support for recovery of cancer.

### Conclusion:

Despite the fact that there are several difficulties to be addressed, medical imaging is one of them. A major changer in imaging, changing from traditional visual analysis to a more objective and automated method analysis by automatically combining imaging biomarkers. Medical imaging, which is generated from imaging data to clinical, genomes, and/or proteomics data, provides enormous potential to improve health. capture the behavior of the tumour. Medical imaging offers promise to better capture the entire disease heterogeneity and provide a novel tool to predict tumour aggressiveness in ovarian cancer as well as the therapeutic response. Thus this paper provides a complete view on the entire imaging medical imaging process utilized in the ovarian cancer phase wise.

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