Volume 9, Issue 5, May – 2024 International Journal of Innovative Science and Research Technology
ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24MAY989

Artificial Intelligence in Early Detection of Cervical Intraepithelial Neoplasia

Lalasa Mukku[1*]; Jyothi Thomas[2]
Research Scholar[1]; Associate Professor[2]
CHRIST (Deemed to be University), Kengeri, Bangalore – India 560074

Abstract:- Artificial Intelligence (AI) is a quickly evolving field of technology used to develop intelligent machines capable of performing tasks such as problem solving, decision making , perception, language processing, and learning. This paper explores the application of AI in the field of gynecological oncology, specifically in the diagnosis of cervical cancer. The paper proposes a hybrid AI model that uses a Gaussian mixture model and a deep learning model to segment and classifies colposcope images. The model performed with satisfactory segmentation metrics of sensitivity, specificity, dice index, and Jaccard index of 0.976, 0.989, 0.954, and 0.856, respectively. This model aims to accurately classify cancer and non-cancer cases from a colposcope image. The results showed that this method could effectively segment the colposcopy images and extract the cervix region. This can be a valuable tool for automated cancer diagnosis and can help improve the diagnosis's accuracy.

Keywords:- *Cervical Cancer, Gyno Oncology, Artificial Intelligence, Machine Learning, Gaussian Models.*

I. INTRODUCTION

Artificial Intelligence (AI) refers to a branch of technology that enables machines to perform tasks that resemble those of humans. [1]. AI mimics human intelligence [2] and is capable of performing tasks such as problem solving, decision-making, perception, language processing, and vision-based learning [3]. In the medical field, AI can be used to diagnose and treat diseases more accurately [4][5], predict patient outcomes [6], and offer personalized treatments [7]. AI research is divided into elemental subfields, mainly Robotics, Machine Learning, Computer Vision, Intelligent Agents and Natural Language Processing [2].

AI is playing an increasingly important role in medical image processing [8]. AI algorithms can be used to automatically analyze and interpret medical images, which can help clinicians with diagnostic decision making [9].

The use of AI in the field of gynecological oncology [10] has gained traction in the past couple of decades [11]. Diagnosis of endometriosis [12] vaginal cancer, ovarian abnormalities [13][14][15][16], uterine cancer [17], cervical cancer [18][19][20][21] and vulvar cancer [22] have all been benefited by deep learning models and machine learning.

Cervical cancer is a prevalent form of cancer among women and is a major cause of death in many developing countries [23]. Human papillomavirus, if not treated properly and in a timely manner, can lead to this type of cancer [24]. The infection turns malignant over a span of five years [24]. Since there is no genetic synergy, cancer can be treated completely in a single clinical visit if diagnosed in its early stages [25][26]. Timely diagnosis of cervical cancer can save lives and significantly reduce the burden of the disease. Certain image details are key to identifying cancer candidates. For example, Squamocolumnar junction visibility, Adequacy, Transformation zone, Metaplastic squamous epithelium, Columnar epithelium, Original squamous epithelium level, and Deciduosis in pregnancy applicability are some factors that are checked before making a diagnosis.

Routine methods of screening include HPV test, pap smear microscopic test [27], visual inspection by acetic acid (VIA) [28], and colposcopy test [29]. Analyzing colposcope images to diagnose cervical cancer is considered to be the gold standard due to the relatively lower financial resource requirement and accurately visible cervix[30]. However, it requires experienced expert personnel to make a decision on diagnosis based on cervix images. In a study by __, the researchers reported 63% accuracy in a biopsy test, indicating a high amount of false positives in primary screening methods like pap and VIA. Another study by __ found that experience of the clinician holds more sensitivity than the station. It was seen that nurses with over five years of experience have significantly higher accuracy in diagnosing colposcope images than first-year PG medical students. A sample image of a colposcope is presented in figure 1.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24MAY989

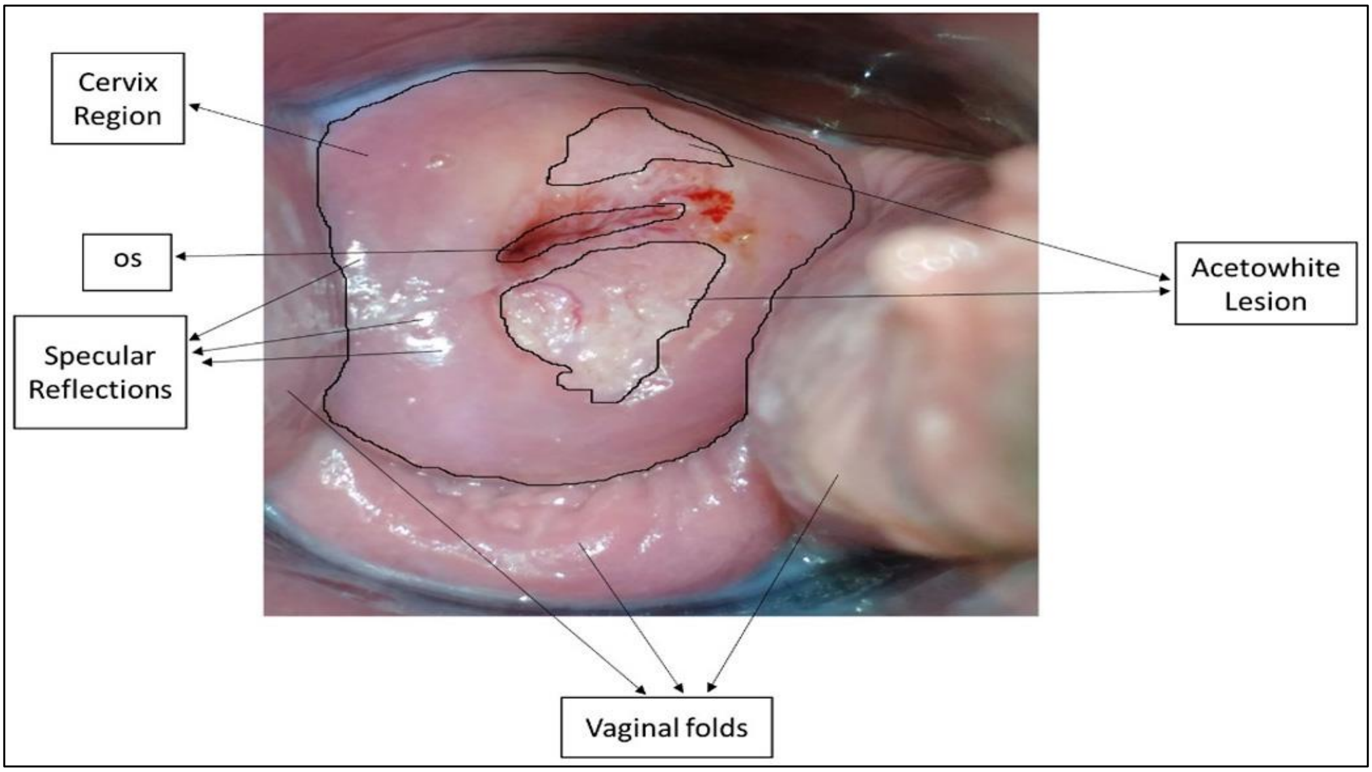

Fig 1: Colposcope Image

Therefore, there is a need to develop a system that can potentially aid clinicians' decisions with a certain degree of confidence. AI has the capability to develop such systems which can classify cancer without human intervention. Deep learning and machine learning are fields of artificial intelligence employed to make medical decision support systems based on clinical data and medical images.

Currently, there is a wide range of computational methods to classify cervical intraepithelial neoplasia from the cervix images. Methods like SVM [31], neural networks [32], K means [33], and mask R-CNN [34] have all proven to be reliable diagnostic algorithms. However, the studies dedicated to classifying the cervigrams frequently overlooked the segmentation of the cervix region of interest from the complete picture [35]. The goal of this study is to develop an artificial intelligence model that can accurately classify cancer and benign cases from cervigram images.

In a colposcope picture, the cervix region, surrounding vaginal walls, and sometimes the speculum device is present. In order to build an AI model to classify the cervigrams, it is essential to segment the cervix region to remove surrounding noise. Figure 2 displays the cervix region marked for ground truth. A potential issue with automated classification is the presence of specular reflections caused by moisture on the organ reflecting the probe's light. [36][37]. The objective of this study is to build a hybrid model that uses AI methods from deep learning and machine learning to segment and classify the colposcope images. A popular machine learning method called the Gaussian mixture model [38] is used to segment the images post and the segmented images are classified using a machine learning model.

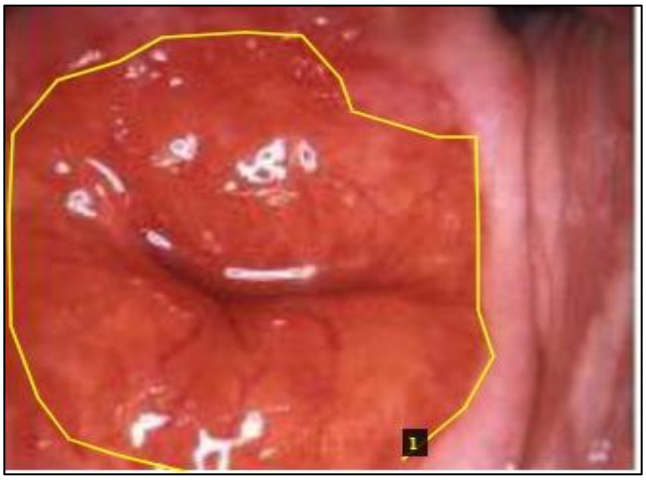

Fig 2: Cervix Region Delineated from the Vaginal Walls and Speculum Space

II. MATERIALS AND METHODS

Dataset: The dataset for this study was collected from two sources: The government maternity hospital in Tirupati, India, and the international agencies for research on cancer (IARC) colposcopy image bank. The IARC Cervical Cancer Image Bank collects images from various clinical settings. Retrospectively collected images are allowed to be included in the image bank only if the image collection process and image quality meet strict eligibility criteria. Images are evaluated by a panel of experts before inclusion in the image bank. Images collected in collaboration with a government maternity hospital were directly taken from the department of gynecology. The hospital provided the collected colposcopy images with corresponding clinical findings.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24MAY989

Some critical attributes of a colposcope image are a) HPV Infection, b) Squamocolumnar junction visibility, c) Adequacy, d) Transformation zone, e) Original squamous epithelium level, f) Columnar epithelium, g) Metaplastic squamous epithelium, h) Deciduosis in pregnancy applicability.

The above information corresponding to every image is recorded in the hospital. This acts as additional input to the machine learning model, enabling a seamless artificial intelligent diagnostic decision. The dataset was split into 80:20 ratios for training and testing the model, which is standard protocol in building machine learning models.

A Gaussian mixture model [39] is a probabilistic model that is based on the assumption that the data instances are generated from a Gaussian distribution [40]. Over the years, it has been used to segment [41], classify [42], and cluster [43] many medical images like CT, MRI, Biopsy images, and X-rays. This model is capable of segmenting the key areas of images and extracting them for clear analysis. Once the unnecessary surrounding areas are cropped, it is easier to interpret the image to diagnose cancer. We are applying a clustering-based gaussian mixture model to segment the colposcope image to extract the cervix region. An ideally cropped image is displayed in figure 3.

The cluster number' k' is taken as two because we are splitting the image into two regions of the cervix and its surroundings. A soft clustering using the gaussian mixture model works by estimating the likelihood of a pixel belonging to either of the clusters.

In this study, the image is given as input to a multivariate gaussian distribution. Multivariate gaussian distribution is an extension of the univariate model that can fit vectors, which are the pixels in this case. X is an input vector with 'd' values. The distribution is parameterized by mean μ (a length' d' vector) and a covariance matrix Σ (d x d matrix). Subsequently, the equation of the probability density function is given by:

$$P(x;\mu,\Sigma) = \frac{1}{(2\pi)^{D/2}|\Sigma|^{1/2}} exp\left(\frac{-1}{2}(x-\mu)^T\Sigma^{-1}(x-\mu)\right)$$

Where:

$\frac{1}{(2\pi)^{D/2}|\Sigma|^{1/2}}$ is a constant that ensures the integral value is 1.

(x- μ): *row vector*

Σ^{-1}: *d* x *d matrix*

$(x-\mu)^T$ is a *column vector*

μ: *weighted mean*, which is a length 'd' row vector

Σ: variance, a *d* x *d* matrix

|Σ|: matrix determinant

The updated mean $\hat{\mu}$ is the imperial average of the pixel vectors in X. It is calculated by $\hat{\mu} = \frac{1}{m}\sum_j x^j$. The covariance matrix Σ is also the empirical average of the vector product calculated by $\hat{\Sigma} = \frac{1}{m}\sum_j(\underline{x}^{(j)} - \underline{\hat{\mu}})^T(\underline{x}^{(j)} - \underline{\hat{\mu}})$. The product of (x- μ), Σ^{-1}, $(x-\mu)^T$ gives a scalar number which is the probability or likelihood of the value 'x' belonging in the cluster k. These parameters were optimized using a metaheuristic algorithm called Mexican axolotl.

Fig 3: Segmented Cervix Image

The models were built on packages like opencv [44] in python and labelme software [45]. The epochs were set to 40, and the model reached the best accuracy at the 32nd epoch. The framework achieved sensitivity, specificity, dice index, and Jaccard index values to be 0.976, 0.989, 0.954, and 0.856, respectively.

For the classification, an ImageNet model, AlexNet is employed. AlexNet comprises five convolutional layers followed by three fully connected layers. It is renowned for its ability to learn complex features from images. The convolutional layers are equipped to extract hierarchical features, while the fully connected layers enable high-level abstraction for classification. The use of rectified linear units (ReLUs) and dropout layers aids in preventing overfitting.

III. RESULTS

The input data was collected from two sources of the government maternity hospital, Tirupati and IARC. The images were pre-processed to remove the specular reflections since they mimic the acetowhite lesions, which are key indicators of cancer. Subsequently, the images were cropped using a gaussian mixture model. Finally, the segmented cervix images were classified using a ML algorithm support vector machine (SVM) [46]. To validate the segmentation process, we deployed the SVM classifier before segmentation and compared it with pictures attained after segmentation. The results show an improvement in accuracy, reaching up to 92.8%. Previous research has already tested the efficiency of machine learning models in cases like rectosigmoid deep endometriosis [12] and confirmed the results. In the current study, the gaussian model exhibited satisfactory results. The SVM performed with an accuracy of 92.8%. Our model has

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24MAY989

been compared to similar studies. It has outperformed other models. This asserts the potential of the model.

IV. DISCUSSION

The present study is a preliminary attempt at analyzing colposcope images for early detection of cervical cancer with the help of artificial intelligence. This article presents the first stage of the analysis, segmentation. As an extension to this research, experimental work is being conducted to identify the best method to diagnose levels of CIN using AI.

Nevertheless, AI has demonstrated usefulness in obstetrics, like determining the chance of preterm birth or a fetus [47], prediction of vaginal delivery [48] etc. As for gynecology, AI has proven to be successful in the automatic classification of ovarian cysts [49], evaluation of myometrium [50] etc.

Overall, The findings of this investigation point to our model being a potential asset in the early recognition of cervical cancer. The model could be utilized to enhance the precision of diagnosis and minimize the amount of time and cost associated with manual image segmentation and classification. Furthermore, the model may be able to aid in the early identification of lesions that pose a risk for developing cervical cancer.

Further investigation is needed to fully assess the capabilities of this model. For example, it is necessary to measure the model's performance on a broader dataset and to contrast it to current methods for segmentation and classification.

V. CONCLUSION

The research presented in this paper has demonstrated the potential of using an artificial intelligence model to automate the analysis of colposcope images for early cervical cancer detection. The model was based on the machine learning concept of gaussian mixture models and SVM for segmenting and classifying the images, respectively. The model performed with satisfactory segmentation metrics of sensitivity, specificity, dice index, and Jaccard index of 0.976, 0.989, 0.954, and 0.856, respectively. The SVM was deployed before the segmentation which was performed with 74% accuracy. The classification after segmentation has resulted in 92.8% accuracy. Specifically, we have shown that our model is capable of achieving significant accuracy when segmenting and classifying images.Furthermore, our model achieved a notable level of precision in identifying and categorizing lesions, which is essential for detecting cervical cancer at an early stage. This research serves as a basis for further progress in the field of AI for the segmentation and classification of medical images. Ultimately, this research can help improve early cervical cancer detection and improve patient outcomes.

ACKNOWLEDGMENTS

The authors acknowledge help extended by the government maternity hospital, Tirupati, in data collection.

- **Conflict of Interest:** None

- **Data Statement:** Data will be shared upon appropriate requests.

REFERENCES

[1]. Finlay J. An introduction to artificial intelligence. Crc Press; 2020.
[2]. Bellman R. An introduction to artificial intelligence: can computers think? Thomson Course Technology; 1978.
[3]. Shukla Shubhendu S, Vijay J. Applicability of artificial intelligence in different fields of life. Int J Sci Eng Res 2013;1:28–35.
[4]. Davenport T, Kalakota R. The potential for artificial intelligence in healthcare. Futur Healthc J 2019;6:94.
[5]. Yeasmin S. Benefits of artificial intelligence in medicine. 2019 2nd Int. Conf. Comput. Appl. Inf. Secur., IEEE; 2019, p. 1–6.
[6]. Chen H-Y, Ge P, Liu J-Y, Qu J-L, Bao F, Xu C-M, et al. Artificial intelligence: Emerging player in the diagnosis and treatment of digestive disease. World J Gastroenterol 2022;28:2152.
[7]. Schork NJ. Artificial intelligence and personalized medicine. Precis Med Cancer Ther 2019:265–83.
[8]. Noguerol TM, Paulano-Godino F, Martín-Valdivia MT, Menias CO, Luna A. Strengths, weaknesses, opportunities, and threats analysis of artificial intelligence and machine learning applications in radiology. J Am Coll Radiol 2019;16:1239–47.
[9]. Recht MP, Dewey M, Dreyer K, Langlotz C, Niessen W, Prainsack B, et al. Integrating artificial intelligence into the clinical practice of radiology: challenges and recommendations. Eur Radiol 2020;30:3576–84.
[10]. Mysona DP, Kapp DS, Rohatgi A, Lee D, Mann AK, Tran P, et al. Applying artificial intelligence to gynecologic oncology: a review. Obstet Gynecol Surv 2021;76:292–301.
[11]. Emin EI, Emin E, Papalois A, Willmott F, Clarke S, Sideris M. Artificial intelligence in obstetrics and gynaecology: is this the way forward? In Vivo (Brooklyn) 2019;33:1547–51.
[12]. Guerriero S, Pascual M, Ajossa S, Neri M, Musa E, Graupera B, et al. Artificial intelligence (AI) in the detection of rectosigmoid deep endometriosis. Eur J Obstet Gynecol Reprod Biol 2021;261:29–33.
[13]. Akazawa M, Hashimoto K. Artificial intelligence in ovarian cancer diagnosis. Anticancer Res 2020;40:4795–800.
[14]. Timmerman D, Verrelst H, Bourne TH, De Moor B, Collins WP, Vergote I, et al. Artificial neural network models for the preoperative discrimination between malignant and benign adnexal masses. Ultrasound Obstet Gynecol Off J Int Soc Ultrasound Obstet Gynecol 1999;13:17–25.

[15]. Acharya UR, Molinari F, Sree SV, Swapna G, Saba L, Guerriero S, et al. Ovarian tissue characterization in ultrasound: a review. Technol Cancer Res Treat 2015;14:251–61.

[16]. Acharya UR, Saba L, Molinari F, Guerriero S, Suri JS. Ovarian tumor characterization and classification: A class of GyneScan™ systems. 2012 Annu. Int. Conf. IEEE Eng. Med. Biol. Soc., IEEE; 2012, p. 4446–9.

[17]. Toğaçar M. Detection of segmented uterine cancer images by Hotspot Detection method using deep learning models, Pigeon-Inspired Optimization, types-based dominant activation selection approaches. Comput Biol Med 2021;136:104659.

[18]. Hu L, Bell D, Antani S, Xue Z, Yu K, Horning MP, et al. An Observational Study of Deep Learning and Automated Evaluation of Cervical Images for Cancer Screening. JNCI J Natl Cancer Inst 2019;111:923–32. https://doi.org/10.1093/jnci/djy225.

[19]. M. S, K. H, A. H, Y. M, K. K, K. T, et al. application of deep learning to the classification of images from colposcopy. Oncol Lett 2018;15:3518–23.

[20]. Perkins R, Jeronimo J, Hammer A, Novetsky A, Guido R, del Pino M, et al. Comparison of accuracy and reproducibility of colposcopic impression based on a single image versus a two-minute time series of colposcopic images. Gynecol Oncol 2022;167:89–95. https://doi.org/https://doi.org/10.1016/j.ygyno.2022.08.001.

[21]. Singh Y, Srivastava D, Chandranand PS, Singh S. Algorithms for screening of Cervical Cancer: A chronological review. ArXiv 2018;abs/1811.0.

[22]. Fragomeni SM, Moro F, Palluzzi F, Federico A, Bove S, Mascilini F, et al. 2022-RA-1299-ESGO How to predict preoperative risk of lymph node metastasis in vulvar cancer patients the Morphonode Predictive Model 2022.

[23]. Sung H, Ferlay J, Siegel RL, Laversanne M, Soerjomataram I, Jemal A, et al. Global Cancer Statistics 2020: GLOBOCAN Estimates of Incidence and Mortality Worldwide for 36 Cancers in 185 Countries. CA Cancer J Clin 2021;71:209–49. https://doi.org/10.3322/caac.21660.

[24]. Rodríguez AC, Schiffman M, Herrero R, Hildesheim A, Bratti C, Sherman ME, et al. Longitudinal study of human papillomavirus persistence and cervical intraepithelial neoplasia grade 2/3: critical role of duration of infection. J Natl Cancer Inst 2010;102:315–24. https://doi.org/10.1093/jnci/djq001.

[25]. Denny L, Quinn M, Sankaranarayanan R. Screening for cervical cancer in developing countries. Vaccine 2006;24:S71–7.

[26]. Goldie SJ, Gaffikin L, Goldhaber-Fiebert JD, Gordillo-Tobar A, Levin C, Mahé C, et al. Cost-effectiveness of cervical-cancer screening in five developing countries. N Engl J Med 2005;353:2158–68.

[27]. Ragothaman S, Narasimhan S, Basavaraj MG, Dewar R. Unsupervised Segmentation of Cervical Cell Images Using Gaussian Mixture Model. IEEE Comput Soc Conf Comput Vis Pattern Recognit Work 2016:1374–9. https://doi.org/10.1109/CVPRW.2016.173.

[28]. Kim E, Huang X. A data driven approach to cervigram image analysis and classification. Lect Notes Comput Vis Biomech 2013;6:1–13. https://doi.org/10.1007/978-94-007-5389-1_1.

[29]. Fang S, Yang J, Wang M, Liu C, Liu S. An Improved Image Classification Method for Cervical Precancerous Lesions Based on ShuffleNet. Comput Intell Neurosci 2022;2022:9675628. https://doi.org/10.1155/2022/9675628.

[30]. Asiedu M, Ramanujam N, Sapiro G. Methods for automated detection of cervical pre-cancers with a low-cost, point-of-care, pocket colposcope 2021.

[31]. Moldovan D. Cervical cancer diagnosis using a chicken swarm optimization based machine learning method. 2020 8th E-Health Bioeng Conf EHB 2020 2020:0–3. https://doi.org/10.1109/EHB50910.2020.09280215.

[32]. Liu L, Wang Y, Liu X, Han S, Jia L, Meng L, et al. Computer-aided diagnostic system based on deep learning for classifying colposcopy images. Ann Transl Med 2021;9. https://doi.org/10.21037/atm-21-885.

[33]. Peng G, Dong H, Liang T, Li L, Liu J. Diagnosis of cervical precancerous lesions based on multimodal feature changes. Comput Biol Med 2021;130:104209. https://doi.org/https://doi.org/10.1016/j.compbiomed.2021.104209.

[34]. Ma S, Huang Y, Che X, Gu R. Faster RCNN-based detection of cervical spinal cord injury and disc degeneration. J Appl Clin Med Phys 2020;21:235–43. https://doi.org/10.1002/acm2.13001.

[35]. Li Y, Chen J, Xue P, Tang C, Chang J, Chu C, et al. Computer-Aided Cervical Cancer Diagnosis Using Time-Lapsed Colposcopic Images. IEEE Trans Med Imaging 2020;39. https://doi.org/10.1109/TMI.2020.2994778.

[36]. Meslouhi O El, Kardouchi M, Allali H, Gadi T, Benkaddour YA. Automatic detection and inpainting of specular reflections for colposcopic images. Open Comput Sci 2011;1:341–54. https://doi.org/10.2478/s13537-011-0020-2.

[37]. Greenspan H, Gordon S, Zimmerman G, Lotenberg S, Jeronimo J, Antani S, et al. Automatic detection of anatomical landmarks in uterine cervix images. IEEE Trans Med Imaging 2009;28:454–68. https://doi.org/10.1109/TMI.2008.2007823.

[38]. RamaPraba PS, Ranganathan H. Automatic lesion detection in colposcopy cervix images based on statistical features. Commun Comput Inf Sci 2012;270 CCIS:424–30. https://doi.org/10.1007/978-3-642-29216-3_46.

[39]. Reynolds DA. Gaussian mixture models. Encycl Biometrics 2009;741.

[40]. Do CB. The multivariate Gaussian distribution. Sect Notes, Lect Mach Learn CS 2008;229.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24MAY989

[41]. Wang L, Chen Y, Pan X, Hong X, Xia D. Level set segmentation of brain magnetic resonance images based on local Gaussian distribution fitting energy. J Neurosci Methods 2010;188:316–25.
[42]. Song D, Kim E, Huang X, Patruno J, Muñoz-Avila H, Heflin J, et al. Multimodal entity coreference for cervical dysplasia diagnosis. IEEE Trans Med Imaging 2014;34:229–45.
[43]. Kageyama S, Mori N, Mugikura S, Tokunaga H, Takase K. Gaussian mixture model-based cluster analysis of apparent diffusion coefficient values: a novel approach to evaluate uterine endometrioid carcinoma grade. Eur Radiol 2021;31:55–64.
[44]. Pulli K, Baksheev A, Kornyakov K, Eruhimov V. Real-time computer vision with OpenCV. Commun ACM 2012;55:61–9.
[45]. Torralba A, Russell BC, Yuen J. Labelme: Online image annotation and applications. Proc IEEE 2010;98:1467–84.
[46]. Suthaharan S, Suthaharan S. Support vector machine. Mach Learn Model Algorithms Big Data Classif Think with Examples Eff Learn 2016:207–35.
[47]. Thomas J, Kulanthaivel G. Preterm Birth Prediction Using Cuckoo Search Based Fuzzy Min-Max Neural Network. Int Rev Comput Softw 2013;8:1854–62.
[48]. Lipschuetz M, Guedalia J, Rottenstreich A, Persky MN, Cohen SM, Kabiri D, et al. Prediction of vaginal birth after cesarean deliveries using machine learning. Am J Obstet Gynecol 2020;222:613-e1.
[49]. Akter L, Akhter N. Ovarian cancer prediction from ovarian cysts based on TVUS using machine learning algorithms. Proc. Int. Conf. Big Data, IoT, Mach. Learn. BIM 2021, Springer; 2022, p. 51–61.
[50]. Stanzione A, Cuocolo R, Del Grosso R, Nardiello A, Romeo V, Travaglino A, et al. Deep myometrial infiltration of endometrial cancer on MRI: A radiomics-powered machine learning pilot study. Acad Radiol 2021;28:737–44.