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| RESEARCH ARTICLE

An Analysis of Cervical Cancer using the Application of AI and Machine Learning

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| ABSTRACT
Cervical cancer, a prevalent malignant neoplasm affecting the female reproductive system, is recognized globally as a prominent contributor to female mortality. Time-to-event analysis, essentially for all the clinical research, was found to be done by the survival prediction method very effectively. There is no screening and other preventive measures at hand and that is why cervical cancer is among the most urgent problems in a developing world. Cervical cancer will be covered in this article covering causes of its emergence, progression, symptoms, and its detection ways. It emphasizes the role played by machine learning in prediction and diagnosis of cervical cancer early, thus indicating the importance of preventive measures. Multiple machine learning algorithms including different approaches for cervical cancer prediction are studied which will include their pros and cons through an exhaustive literature analysis. Improved accuracy and clinical applicability should be the main objectives of this field, and this review helps to demonstrate the research gaps as well as the importance of integrating multiple data types, using a representative dataset, improving model understandability and implementing a holistic evaluation model. It is imperative that researchers fill the gaps in their models by collecting multi-modal data, using bigger and more relevant datasets and by designing models that are amenable to understanding, and creating reliable standards to appraise the outcomes. Moreover, the focus should be laid on the implementation and verification of predictive models in real-life clinical situations, so that they can assess their true value for cervical cancer prevention and patients' results.

| KEYWORDS

Cervical cancer, diagnosis, prediction, risk factor, machine learning, HPV.

| ARTICLE INFORMATION

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1. Introduction
The unpredictable nature of problems introduces an element of adversity into the human condition. Women often face a number of challenges during their lives. Cervical cancer is one of the most serious illnesses people might have, and it creates a lot of issues [1]. The fact that women don't realize how important it is to discover uterine cancer early is the main reason why the disease strikes at an older age [2]. Cervical cancer poses a significant global health risk to women, and the early indicators of this disease are often challenging to identify [3]. Its progressive dissemination to other anatomical sites, including the liver, lungs, and vagina, may exacerbate the challenges associated with the condition, which inflicts damage upon deep cervix tissues [4]. Nevertheless, despite the gradual progression of cervical cancer, advancements in precancerous technology have facilitated its early detection, prevention, and treatment. The incidence of cervical cancer has decreased in a majority of countries over the last few decades due to advancements in detection technologies. 4290 deaths are anticipated to be attributed to cervical cancer this year [5]. Cervical cancer has been detected earlier as a result of improved screening methods, which have contributed to a reduction in the mortality rate by about half since the mid-1970s. 1996–2003 witnessed an annual mortality rate in excess of 4%; 2009–2018, it fell below 1%. The pre-invasive phases of uterine cervical cancer persist for an extended period of time. Through a successful treatment of precancerous-stage lesions detected by screening tests, cancer can be prevented. However, it has been established that underdeveloped nations have an exceptionally high mortality rate due to their lack of access to state-funded preventive measures, including national assessment programs and free immunization initiatives.

Cervical cancer becomes an untreated consequence of a human papillomavirus (HPV) infection of a cervix [6]. In cervical cancer, the prevalent infectious agent is HPV because of its ability to promote neoplastic development. The malignant phase of cervical cancer is characterized by neoplastic development, which is an abnormal proliferation of cells and an abnormal multiplicity of cells [7]. Consistently, the healthcare sector generates vast quantities of data from which information can be extracted to predict future disease by analyzing a patient's health data and treatment history. In addition, each of these domains can be improved through the utilization of vital healthcare data. In healthcare, machine learning facilitates the analysis of immense quantities of complex medical data in order to derive therapeutic insights. Then, doctors can apply this knowledge to the delivery of medical treatment. Consequently, the implementation of ML in healthcare has the potential to enhance patient satisfaction. This research endeavored to identify algorithms that exhibit superior suitability for clinical application in the classification of negative and positive cervical cancer. The utilization of such algorithms enables the detection of cervical cancer.

2. Overview of Cervical Cancer

Among the main reasons why women die, cervical cancer surely ranks high. An thorough investigation found that 85 percent of cervical cancer patients in third-world nations are discovered at an early stage. A straightforward reason for this alarmingly high ratio is the unavailability of the required fundamental medical resources in the regions [8]. Countries with modern medical resources aim at preventing cervical cancer by providing cervical cancer screening systems to detect precancerous cells than can lead to invasive cancer. Worldwide, pap smear testing has the highest rate of cervical cancer screenings. Cervical cancer screening methods have traditionally focused on detecting malignant and precancerous lesions in industrialized nations. Cervical cancer incidence has decreased by 80% in certain Nordic countries since the implementation of screening systems. It has decreased by 65 percent over the past four decades, and cervical cancer incidence and mortality rates in Sweden have remained stable over the past decade. In third world country Pakistan, cervical cancer is listed third major cause of morality amongst women across all age groups. The mortality figures are high because of ignorance in terms of screening and prevention in Pakistan. According to a detailed survey it was observed that 70% of the cervical cancer are diagnosed at the advanced stage of malignancy which is the cause high mortality figures in the third world country like Pakistan [9].

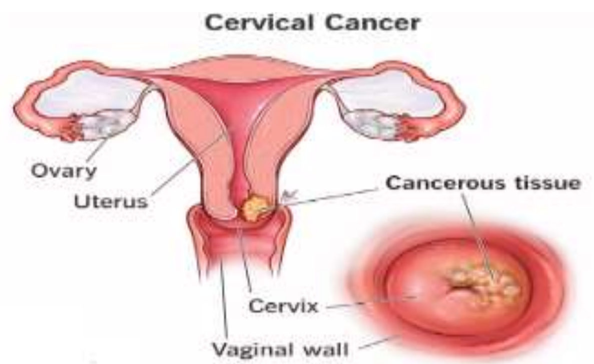

Fig. 1. Cervical cancer

Cervical cancer affects the cervix, the anatomical structure located at the level of the uterus and vagina in females. Generally cancers are abnormal changes in the cell growth which happens in human body. Cervical cancer is also reported as an abnormal cell changes in the path to uterus or in the entrance to the womb. Normally, this condition is called as dysplasia. These changes in the cervix, will take several years to form as cancer cells. These kinds of abnormal cell changes can be detected through a screening test and discover the type of cell changes. Women with cervical cancer may not show any symptoms in initial stage. Symptoms often divulge only in the final stage, where there is an enormous growth of abnormal cells in the cervix. Some of these symptoms include: irregular or inter menstrual periods, pain after sexual intercourse, pain in the leg or in pelvic regions, an unusual vaginal discomfort or vaginal discharge. Since there are no symptoms revealed in the earlier stage, it is important to meet the doctor for a periodical screening test in order to prevent oneself from fatality.

2.1 Risk factors for cervical cancer

Something which amplifies the risk or possibility of incidence of a disease is called risk factor. It does not mean that having one or more risk factors will definitely have the disease. Mostly different diseases have different causes and risk factors. Some of the common risk factor for cervical cancer is discussed here.

Fig. 2. Risk factor of Cervical cancer

1) Infection with HPV

There are more than 150 types of HPV viruses exist. Out of these, only 15 types of viruses are contributing to the risk of cervical cancer. HPV can spread person to person through skin contact especially during the sexual activity. Certain types of viruses are low risk types of HPV which mostly occurs in female or male genitals. High-risk types of HPV are strongly connected to cancer, which includes cervical cancer, vulvar cancer and vaginal cancer.

2) Sexual Activity

Genital skin-to-skin contact and/or oral intercourse shall be defined as included. Cervical cancer poses a liability for all women who have ever engaged in sexual activity. Rarely are women who have never had intercourse diagnosed with cervical cancer. Due to the vasculature's transformations that occur during puberty, early sexual activity can elevate a risk of developing cervical cancer. These modifications heighten a region's susceptibility to harm.

3) Smoking

Tobacco vapor contains at least seventy carcinogenic compounds, or carcinogens. Engaging in smoking elevates the likelihood that an HPV infection will persist indefinitely. Cervical cancer incidence was found to be higher among women who were both smokers and those who were exposed to secondhand smoke, even after controlling for other variables like sexual activity. Women who were exposed to three or more hours of smoke per day have a risk of developing cervical cancer that is approximately three times greater, while current smokers have a risk that is 3.4 times greater [10].

4) Chlamydia Infection

Chlamydia is a relatively prevalent species of bacterium that causes infections of the reproductive system. It spreads generally via the sexual contact. Only when the pelvic of the woman is examined, the infection of the Chlamydia can be identified. Generally this doesn't show a symptom to diagnose the infection. Chlamydia infection causes pelvic inflammation which in turn leads to infertility in many cases [11].

5) Having Multiple Full-Term Pregnancies

Women who have experienced over three complete pregnancies have an elevated likelihood of developing cervical cancer, according to the available cases. As a result of the increased risk of HPV infection and sexual activity, it is being considered. Additionally, research has linked hormonal fluctuations that occur during pregnancy to an increased vulnerability of women to HPV infection, consequently elevating the risk of cancer progression. Hormonal changes could be responsible for making a woman susceptible to HPV infection and cancer growth [12].

6) Long-Term Use Birth Control Pills

There is data that suggests that the risk of acquiring cervical cancer is higher in women who take oral contraceptives (OC) for several years. A higher incidence of cervical cancer is associated with long-term OC usage (five years or more) compared to non-users [13]. Use of OC for longer periods of time is associated with an increased risk of cervical cancer. A 10% increased risk was observed in one research for use of less than five years, a 60% increased risk was found for use of five to nine years, and the risk doubled with use of ten years or more. Nevertheless, research has demonstrated that the incidence of cervical cancer gradually diminishes once women discontinue oral contraceptive use [14].

7) Genetic Susceptibility

Genome-wide association studies and twin and other first-degree relative investigations have shown genetic vulnerability to HPV-caused cervical malignancies. Compared to women who have no biologic first-degree family with a cervical cancer, women who have an afflicted first-degree relative are at a 2-fold higher relative risk of acquiring a cervical tumor. The cause of fewer than 1% of cervical cancers is genetic predisposition.

8) Weakened Immune System

The AIDS-causing HIV weakens an immune system and increases a likelihood of HPV infections in women. However, the danger is higher for persons living with HIV, as well as for those whose immune systems are continuously reduced, such as transplant patients, and for those suffering from other acute or chronic illnesses [15]. Cervical cancer is more common in women whose immune systems are compromised.

9) Other Factors

Cervical cancer was more common in women whose mothers had used Diethylstilbestrol (DES), a medicine that was prescribed to certain women between 1940 and 1971 to stop miscarriages. Women who had previously used an intrauterine device (IUD) were less likely to develop cervical cancer, according to new research. Cervical cancer is more prevalent among socioeconomically disadvantaged women, according to the available research. Women from low-income families, Black women, Hispanic women, and American Indian women are more likely to be found in those groups. An elevated risk of cervical cancer may be seen in women whose diet plans are inadequate in providing enough amounts of certain vitamins and minerals. Diabetic cervical cancer is more common in overweight women. Additionally, cervical cancer is more common in women with genital herpes.

2.2 Stages of Cervical Cancer

A four-stage method is most often used to classify cervical cancer [16].

1) Stage 0

It is referred to as Carcinoma in –situ. The tumor has only spread to the epithelium and has not spread to deeper tissues.

2) Stage 1

Stage I carcinoma is confined to the cervix and should not be confused with uterine corpus cancer.

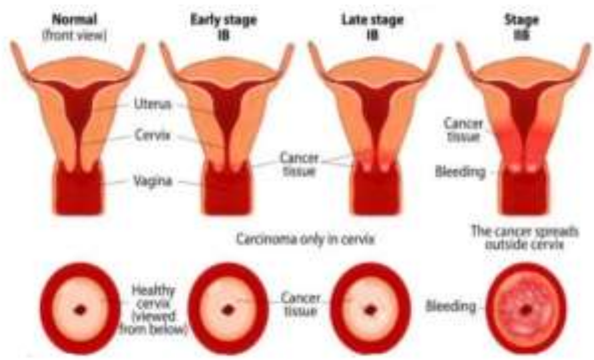

Fig. 3. Stages of cervical cancer

- **Stage IA:** Malignancy detected only under a microscope. An invasion of the stroma measuring no more than 5 mm deep and 7 mm wide is permissible.
- **Stage IB:** Superior to Stage IA or cervix-limited clinical lesions are preclinical lesions. Every visible lesion, even those with just a superficial invasion, is considered a stage IB malignancy. At this stage, they consist of tumors that are visible even without a microscope. It also includes tumors that are larger than 7 mm in diameter and have penetrated more than 5 mm of connective cervical tissue but cannot be detected without a microscope.

3) Stage 2

The second stage of cervical cancer is called stage II carcinoma, and it has spread beyond a cervix but has not yet gone to a pelvic wall. Cancer affects a vaginal wall, but not a lower third.

- **Stage IIA:** There isn't any clear parametric interaction. Up to two-thirds of the vaginal wall is involved.
- **Stage IIB:** Obvious parametrical involvement. Tumor has spread of the tissue next to the cervix, but not into the pelvic sidewall.

4) Stage 3

Stage III cervical cancer has progressed to a pelvic walls. Upon rectal inspection, it is not possible to discern any cancer-free space separating the tumor from the pelvic walls. A portion of the vaginal wall at the base has been invaded by the tumor. Patients with hydronephrosis or renal failure are considered to have stage III cancer.

- **Stage IIIA:** There is no expansion into the pelvic sidewall, although the bottom part of the vagina is involved.
- **Stage IIIB:** Extension of the pelvic diaphragm may result from hydronephrosis, or a malfunctioning kidney.

5) Stage four

Carcinoma in stage IV has met the clinical criteria when it has metastasized beyond a true pelvis or when it has affected a mucosa of a bladder and/or rectum. Cervical cancer has progressed to this level.

- **Stage IVA:** The malignancy has metastasized to nearby organs, including the rectum or bladder. Metabolic metastasis to neighboring organs of the pelvis.
- **Stage IVB:** The tumor has metastasized to anatomical sites distant from the cervix.

A chances of survival increase only if a person who accesses the symptoms at the earliest age and seeks medical attention through a proper screening. An average human being has cells in the body with a set lifespan when the cells die the body regenerates new cells to replace them but cancer is the result of unrestrained splitting up and development of abnormal cells.

2.3 Symptoms of Cervical Cancer

Cervical cancer in its early stages, also known as pre-cancer, causes no symptoms in women. It is difficult to diagnose and thus impossible to treat. However, after 30 years, a woman must continue to observe her own body daily to notice the following signs[17].

- Vaginal leakage that occurs during menstruation, during intercourse, or after menopause.
- Vaginal discharge that does not quit and may be watery, pink, pale, dark-colored, ludicrous, or rotten.
- Bleeding that occurs between regular menstrual periods
- Cervical cancer has the potential to spread to the bladder, digestive tract, lungs, and liver.
- Lower back pressure, pain between hip bones (pelvis), or pain in your lower tummy
- Vaginal leakage of urine or feces

3. Cervical Cancer Screening

There are two diagnostic procedures that may be used to detect cervical cancer early on. One of the first screening methods that is considered the gold standard globally is the Pap smear test, which is also called cytology or the Papanicolaou test. Examining the cells surrounding the cervix's surface for precancerous lesions is a straightforward, non-invasive procedure. Pap smear screening according to conventional practice. An additional examination pertains to the DNA of the HPV, the causative agent of cervical cancer that is universally acknowledged. The HPV test is significantly more expensive than cytology [18]. The implementation of Pap test (or Pap smear) screening has significantly decreased the mortality rate among women who have undergone routine testing in nations that have an efficient screening program [19]. However, the entire procedure is laborious, susceptible to observer bias, and devoid of quantifiable evidence that can be replicated. Therefore, the pathologist will find an automated system for Pap smear screening to be especially beneficial. Cervical cancer is a significant disease that warrants comprehensive research due to its high incidence, preventability potential, and the absence of an automated Pap smear screening system.

The alterations that culminate in cervical cancer progress gradually. Preventative gynecologic examinations may include screening procedures that identify early changes. Pap smear utilization has substantially decreased the mortality rate associated with cervical cancer. Numerous women who undergo Pap smears neglect to return for retesting and treatment. Cervical cancer predominantly affects women who have not undergone routine Pap examinations. Test results are most precise when obtained 12 to 14 days subsequent to the onset of menstruation. Women are advised against douching or engaging in sexual activity for a period of 48 hours following the test. Spermicidal lotions and douches have the potential to eliminate aberrant cells, thereby disrupting the outcomes of a Pap smear. (Douching is generally not advised whatsoever.) While a Pap smear typically does not cause pain, certain women may experience mild discomfort. The following are Pap smear recommendations:

- All sexually active women, irrespective of age, ought to undergo Pap smear testing.
- Adequate medical treatment should be provided to resolve genital infections in order to decrease the incidence of dysplasia.
- Colposcope identification of "at-risk" cervixes is a valuable adjunct to cytology.
- The training curriculum should incorporate preventive oncology, and gynecologists should be assigned to encounters in order to acquire this knowledge.
- It is imperative that every common hospital be equipped with a colposcope.

The Pap smear test exhibits only limited reliability as an indicator of cervical cancer risk in females. Pap smears yield aberrant findings in approximately 10% of cases, but cancer is detected in only about 0.1% of the women who have these results. Anomalies are typically of low grade and lack the propensity to develop into cancer. They may also arise from benign conditions, such as menopause cellular alterations that occur naturally. Vastly utilized for a diagnosis and prognosis of cervical cancer is machine learning.

4. Overview of Machine Learning

ML can be classified as a subfield of AI due to the fact that its algorithms serve as foundational components that teach computers to behave more intelligently through generalization, as opposed to merely storing and retrieving data as in the case of database systems and other applications. Inspiration for machine learning has been derived from numerous academic fields, such as computer science, statistics, biology, and psychology. Machine learning's fundamental purpose is to instruct computers on how to autonomously identify a reliable predictor by leveraging previous experiences; this is accomplished through the utilization of a competent classifier [20]. Its application is primarily limited to intricate problems or tasks that encompass vast quantities of data. It is a viable alternative for handling more intricate data and provides expedited and precise outcomes [21]. It facilitates the identification of profitable opportunities and unforeseen hazards for an organization.

Fig. 4. Machine Learning

There are many parts of ML approaches: Reinforcement, semi-supervised, unsupervised, and supervised [22]. In the following sections, these ML approaches are discussed.

4.1 Supervised Learning

An algorithm constructs a mathematical model in supervised learning using a data set that includes both the desired outputs and the inputs. In other words, the input and desired outputs are specified for the labelled examples utilized to train these algorithms. The learning algorithm is provided with a set of inputs and the corresponding accurate outputs. The algorithm is trained to detect mistakes by comparing its actual output with the right output. Supervised learning makes use of patterns to forecast values; examples include classification, regression, prediction, and gradient boosting. Applications that utilize previous data to forecast future occurrences often use this learning. The supervised learning process carries out two main functions: classification and regression.

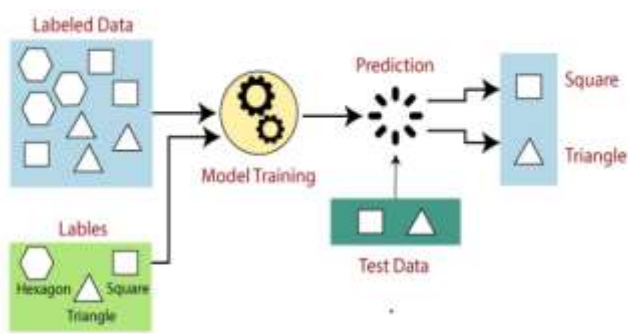

Fig. 5. Supervised learning

4.2 Unsupervised machine learning

Unsupervised learning methods categorize data without labels into similar subsets. It's a strategy used by machine learning programs. Information that is not tagged nor classed is ignored. This frees the system from acting on the data without intervention from a human. Grouping unsorted data according to patterns, differences, and similarities is the work at hand in unsupervised learning, which requires no preexisting knowledge of the data. In unsupervised learning, the computer is not given any training data or human direction. Unsupervised learning methods like labels and clustering are unavailable during the training phase. Opinions are expressed and classified utilizing a set of established syntactic patterns. [23].

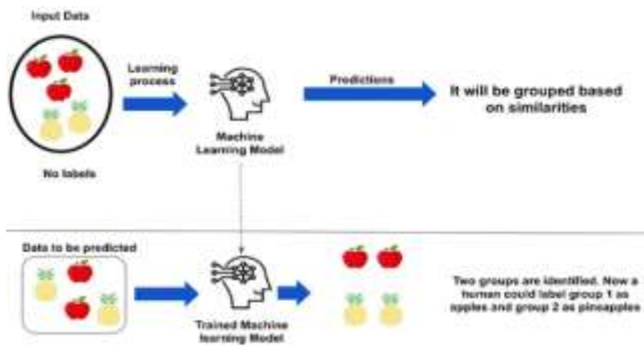

Fig. 6. Unsupervised learning

4.3 Reinforcement learning

The notion of reinforcement learning is founded upon a collection of procedures that, for the most part, execute their tasks sequentially. These techniques are specifically engineered to autonomously assess the optimal operation within a given setting with the intention of optimizing the overall efficacy of the system [24]. A reinforcement method, also known as a "agent," operates at each stage and generates forecasts regarding the subsequent stage's features by utilizing current and past attributes. It is subsequently incentivized or penalized in accordance with its predictions. As a result, it is a highly effective instrument for training AI models, which has the potential to enhance the performance of intricate systems such as supply networks, factories, robotics, and autonomous cars.

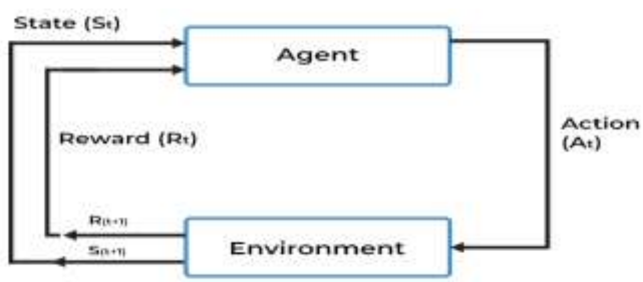

Fig. 7. Reinforcement learning

5. Literature Review

This section gives a review of several ML algorithms. Part, one focuses on the risk factor, part two on the mathematical model, and part three on the machine learning approaches used in the review.

This paper Jaya and Latha, (2020) employing six tiers of Pap images for segmentation, pre-processing, and feature extraction of interest. When comparing SSIM to Fuzzy C-means and K-means algorithms for cancer segmentation, performance measures are used. Therefore, the most effective method for nucleus segmentation in Papsmear images is an one that requires separating the images and then adding the RGB channels for its segmentation. The accuracy level of 94.60% was achieved by employing KNN and SVM classification on 182 Pap smear images with six labels per class. Matlab R2016a isa tool for programmers [25].

In this work Kanitkar *et al.*, (2019) have used object recognition algorithms, namely SSD and Faster-RCNN, to cervix extraction from VIA and VILI test pictures. Cervix segmentation in VIA pictures has also been accomplished using clustering and thresholding, two conventional approaches in image processing. Lastly, they have offered a thorough evaluation and comparison of ML and conventional image processing methods for VIA cervix segmentation, focusing on aspects like execution time, accuracy of abnormality prediction, and better fit [26].

This paper Kurnianingsih *et al.*, (2019) explains a method for batch-wise segmenting cervical cells using a Mask R-CNN and subsequent classification utilizing a smaller VGG-like Net. Applying our suggested approach to the Herlev Pap Smear dataset, we assess its efficacy. During the segmentation phase, the prior segmentation approach was surpassed in precision(0.92±0.06), recall(0.91±0.05), and ZSI(0.91±0.04) by Mask R-CNN when applied to a whole cell. The whole segmented cell is sent through a VGG-like Net during the classification step. The outcome for the binary classification issue is a sensitivity score of more than 96% and a low standard deviation of around 2.8%. Meanwhile, for the 7-class problem, it produces a higher score of over 95%and a low standard deviation of up to 4.2%in accuracy measurement, as measured by h-mean and F1 score [27].

In this paper Song and Du, (2019) they analyze the classification performance on both the data and technique levels, with a focus on the imbalanced labelled picture data. For the purpose of cervical lesion image classification, we use a VGG19 network in conjunction with transfer learning to identify normal (ok), HPV virus infection (hpv), cervical intraepithelial neoplasia (cin), cervicitis (cv), and polyp (polyp). They modify the network topology at the algorithmic level by balancing the weights of the loss function. Each of these approaches is used with a VGG network in turn. Confusion matrix, Accuracy, G-mean, and F-score are the last metrics used to assess the classification performance. Our suggested DA-WB-TL and SMOTE-TL methods are far better than just putting data into a neural network [28].

Prum, Handayani and Boursier, (2018) to classify cell types and identify aberrant cells using a method based on ML. The SVM classifier and HoG feature extraction approach are the backbone of the suggested system. Assuming flawless nucleus detection in every cell picture, the experimental findings showed an identification rate of 94.70%for normal and pathological cell categorization using the Harlev dataset. Our system maintains an identification rate of 88.83% while using our suggested nucleus detection approach in a real-world application [29].

This paper Zhang et al., (2017) solves these problems by suggesting a way to use CNN to directly categorize cervical cells based on deep properties, without the need for previous segmentation. They test the suggested approach on two datasets: Papsmear and LBC. When tested using the Herlev benchmark Papsmear dataset and assessed using five-fold cross-validation, our technique surpassed prior algorithms according to specificity(98.3%),AUC(0.99) values, and classification accuracy(98.3%) [30].

Table 1: Comparative analysis of related work for cervical cancer prediction analysis

Ref	**Proposed work**	**Dataset**	**Key Findings/Results**	**Limitations/future work**
[31]	DL model like CNN	The dataset has been preprocessed and includes 4,337 negative photos and 3,902 positive ones.	73.08% accuracy, AUC of 0.75.	Further development needed for data enhancement and CNN algorithm for more effective diagnostic structure.
[32]	Developed CLDNet model using SE CNN and RPN to detect cervical lesions. Used 6536 colposcopy images for training.	25,67 negative photos and 25,28 positive cervical images out of 6536 colposcopy images.	Average precision of 92.53% and average recall rate of 85.56% in identifying cervical lesions.	Limited to colposcopy images; no differentiation between SIL case studies of low and high quality.
[33]	Used DL networks including Retina Net for evaluating cervical image sharpness.	4525 unidentified images from 1399 females.	Retina Net achieved 98% sensitivity, 85% specificity, and 94% accuracy in image sharpness evaluation.	Limited to assessing image sharpness; not comprehensive for cervical lesion diagnosis.
[34]	Used DL algorithm on longitudinal cohort for cervical screening. Employed Cervigram for detection and classification using R-CNN.	Longitudinal cohort of 9406 females in Costa Rica.	Precancer and cancer cases identified with AUC of 0.91. Limited to CIN2 cases only.	Small sample size, images obtained with film camera, limited number of nurses taking images.
[35]	Implemented fuzzy reasoning model to classify cervical images post-acetic acid test.	The results showed that out of 505 individuals, 383 did not have CIN and 122 did.	Sensitivity and specificity ranged from 80.8% to 87.4% and 80.9% to 86.2% respectively.	Cannot differentiate between low and high-quality SIL cases; limited sample size affecting analyzable features.
[36]	offered three methods for RF segmentation: natural, acetic acid, and Lugol's iodine test	Natural, acetic acid, and Lugol's iodine tests were used to segment ROI.	83.1% accuracy in final diagnosis.	Limited sample size and non-uniform distribution of data.

5.1 Research gap

While machine learning has great promise for improving cervical cancer detection and prognosis, there are still several major holes in the current body of research. To start, predictions may be more accurate and resilient if many data modalities—including clinical, imaging, and genetic data—were integrated more effectively. Firstly, research projects are often based on rather narrow datasets that are almost alike which causes obstacles to extrapolate the findings for diverse healthcare setups and demographics. The fact that DL models possess potential of image-based detection should also be taken into account yet they are not interpretable which they are not accepted by the clinicians. Furthermore, the criteria under consideration deal with the classification performance, with the situation of model uncertainty, and with clinical usefulness almost not being considered. There are multiple dimensions of this problem and the solution will be to try to integrate different data modalities, employ large datasets that represent the general population, improve the model interpretability, and perform a robust evaluation. These efforts are always significant if they have to make way for more refined predictive models that are more accurate, interpretable, and clinically relevant, which in turn will help in decreasing a rate of incorrect diagnoses and advancing earlier cervical cancer diagnosis.

6. Conclusion

Treatment outcomes in the pre- and cancer phases are improved with early identification. Another way to prevent diagnostic delays caused by cervical cancer is to be aware of the symptoms of the disease. Using traditional ML techniques, this study has concentrated on cervical cancer. This paper has been a perfect entry point to the cervical cancer subject which provides the readers with the information about its causes, process as well as with the available methods of detection. Learning about the various algorithms and techniques that researchers use, has been very informative. Machine learning has also shown its relevance in better cervical cancer prediction and detection. Finally, machine learning might emerge as a promising means of improving cervical cancer prediction and diagnosis. Nevertheless, the field faces some challenges, including too specific datasets, integration of other types of data, and models which are difficult to understand and interpret. In the future, more complex data integration, the use of bigger and more representative datasets as well as the creation of interpretable ML models should become the key objectives. It is also critical to consider model implementation in real-world clinical settings and the provision of standard evaluation frameworks because of their impact on cervical cancer prevention and patient outcomes. The resolution of these problems will thus make a real impact on cervical cancer outcomes globally and conduct research in the cervical cancer field.

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