جامعة أبو بكر بلقايد - تلمسان

Abu Bakr Belkaïd University of Tlemcen

Faculty of technology

Department of Biomedical Engineering

Biomedical Engineering Research Laboratory

Final year Project report

In order to obtain the degree of

MASTER in BIOMEDICAL ENGINEERING

Specialty: Medical imaging

Presented by: Zaalani Halima Ines

Automatic detection of cervical cancer

defended on -- October 2024 before the Jury

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Acknowledgments

الحمد لله الذي بنعمته تتم الصالحات

I would like to express my deepest gratitude to all the individuals who have contributed to the completion of this thesis. Firstly, I extend my sincere appreciation to my thesis advisor,

Professor [Youbi Ridha], *for his unwavering support, valuable guidance, and constant availability throughout this journey. His scientific rigor and comprehensive vision have enabled me to grow as a researcher and achieve this outcome.*

I am also grateful to the members of the thesis committee, ***Professor [Kadri Benamar],*** *and* ***Mm [Hedeili Nawel]*** *and* ***M [Manseri Nabil]****, for the honor they have bestowed upon me by accepting to judge this work. Their constructive remarks and insightful questions have allowed me to delve deeper into my research and enhance the quality of my thesis.*

I would also like to express my gratitude to all my colleagues and friends who have supported and encouraged me throughout this endeavor. Their advice, attentiveness, and good humor have kept me motivated and helped me overcome the challenges I faced.

Finally, I extend my heartfelt appreciation to my parents and my sisters also my brother loved ones for their unwavering support and unconditional love. Their presence and encouragement have been an essential source of motivation in completing this work.

Thank you all.

[Zaalani Halima Ines]

[10-10-2024]

Dedication

I would like to express my sincere gratitude to my parents, my mother "Sihem" and my father "Kamel", for all their hard work and unwavering belief in me.

I am also deeply thankful to my sisters "Oumeima" , "Niama" and "Kenza" for being my constant support through thick and thin.

And to my brother, "Abdelhak", who has always been a pillar of strength.

I cannot forget my dear friends, Asmaa, Fatima, and Doua, as well as Noor, who have always been the best companions I could ask for. I am also grateful to my fellow female students who have helped me immensely.

I would like to extend my heartfelt thanks to my colleague from the University of Msila "Ayoub belguellaoui", who has been an invaluable support since the beginning of this work.

Lastly, I want to thank myself for all the hard work, sleepless nights, and sacrifices I have made to reach this point."

Zaalani Halima Ines.

الملخص:

ينشأ سرطان عنق الرحم من نمو خلايا غير طبيعي في عنق الرحم، وهو الجزء السفلي والضيق من الرحم الذي يتصل بالمهبل ويلعب دورًا حيويًا في عملية الولادة. يُعد عنق الرحم معرضًا بشكل خاص للإصابة ، (HPV) بالسرطان نظرًا لتعرضه المتكرر للعدوى، وخاصة تلك التي يسببها فيروس الورم الحليمي البشري والذي ينتقل غالبًا عبر الاتصال الجنسي.

عامل خطر كبير في تطور سرطان عنق الرحم، حيث يمكن أن تُحدث بعض السلالات عالية HPV يُعد الخطورة من الفيروس تغيرات خلوية في عنق الرحم، مما يؤدي في النهاية إلى حدوث أورام خبيثة إذا استمر الفيروس لفترة طويلة.

تنتهي بشكل تلقائي، فإن استمرار العدوى يزيد HPV على الرغم من أن العديد من حالات الإصابة بفيروس من خطر تطور سرطان عنق الرحم، خاصة في الحالات التي لا يتم فيها اكتشاف أو معالجة التغيرات غير الطبيعية في مرحلة مبكرة. يُعد الكشف المبكر أمرًا حاسمًا للعلاج الفعّال، حيث إن سرطان عنق الرحم غالبًا ما يكون بدون أعراض حتى يصل إلى مراحل متقدمة.

في بحثنا، نركز على تطوير طرق اكتشاف سرطان عنق الرحم باستخدام تقنيات معالجة الصور لتحليل صور الخلايا في عنق الرحم. من خلال هذا النهج، نسعى إلى تحسين الدقة وتعزيز الكشف المبكر، مما يدعم في النهاية نتائج أفضل في تشخيص وعلاج سرطان عنق الرحم.

الكلمات المفتاحية: سرطان عنق الرحم، تحليل صور الخلايا، التشخيص بمساعدة الحاسوب، التصوير الطبي

Abstract:

Cervical cancer originates from abnormal cellular growth in the cervix—the lower, narrow end of the uterus that connects to the vagina and plays a vital role in the childbirth process. This region is particularly susceptible to cancer due to its frequent exposure to infections, notably those caused by the human papillomavirus (HPV), which is primarily transmitted through sexual contact. HPV is a significant risk factor in the development of cervical cancer because certain high-risk strains of the virus can induce cellular changes within the cervix, eventually leading to malignancy if the infection persists.

Although many HPV infections resolve on their own, those that persist increase the risk of developing cervical cancer, especially in cases where early-stage abnormalities go undetected or untreated. Early detection is critical for effective treatment, as cervical cancer often remains asymptomatic until reaching advanced stages.

In our research, we focus on advancing cervical cancer detection methods by employing image processing techniques to analyze cervical cell images. Through this approach, we aim to improve accuracy, enhance early-stage detection, and ultimately support better outcomes in cervical cancer diagnosis and treatment.

Key words: Cervical cancer, Cell image analysis, Computer-aided diagnosis, medical imaging.

Résumé:

Le cancer du col de l'utérus provient d'une croissance cellulaire anormale dans le col de l'utérus, la partie inférieure et étroite de l'utérus qui se connecte au vagin et joue un rôle vital dans le processus de l'accouchement. Cette région est particulièrement sensible au cancer en raison de son exposition fréquente aux infections, notamment celles causées par le virus du papillome humain (VPH), principalement transmis par contact sexuel. Le VPH est un facteur de risque important dans le développement du cancer du col de l'utérus, car certaines souches à haut risque du virus peuvent induire des changements cellulaires dans le col de l'utérus, conduisant éventuellement à une malignité si l'infection persiste.

Bien que de nombreuses infections à VPH se résorbent d'elles-mêmes, celles qui persistent augmentent le risque de développer un cancer du col de l'utérus, surtout dans les cas où les anomalies à un stade précoce passent inaperçues ou ne sont pas traitées. La détection précoce est essentielle pour un traitement efficace, car le cancer du col de l'utérus reste souvent asymptomatique jusqu'à des stades avancés.

Dans nos recherches, nous nous concentrons sur l'amélioration des méthodes de détection du cancer du col de l'utérus en utilisant des techniques de traitement d'images pour analyser les images de cellules cervicales. Grâce à cette approche, nous visons à améliorer la précision, à renforcer la détection précoce et, finalement, à soutenir de meilleurs résultats dans le diagnostic et le traitement du cancer du col de l'utérus.

Mots-clés : Cancer du col de l'utérus, Analyse d'images cellulaires, Diagnostic assisté par ordinateur, Imagerie médicale.

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General introduction

General introduction

Cervical cancer remains a major global health issue, particularly affecting women in developing countries where healthcare resources are often limited. Early detection and timely treatment are vital in improving patient outcomes. Traditional screening methods like Pap smears and HPV testing, while effective, can be resource-intensive, costly, and time-consuming, often requiring skilled healthcare professionals and specialized equipment. This poses challenges in settings with limited healthcare infrastructure.

Recent advancements in digital imaging have introduced promising avenues for the automatic detection of cervical cancer. By employing techniques such as morphological analysis and segmentation, algorithms can analyze cervical cell images and identify abnormal cells that could indicate cancer. This approach aims to overcome some of the limitations of conventional methods, offering a faster, more accessible, and potentially more accurate solution.

The primary goals of automatic cervical cancer detection are to:

- **Enhance accuracy:** Achieve higher sensitivity and specificity in detecting cancer cells compared to traditional methods.

- **Increase efficiency:** Minimize the time and cost associated with cervical cancer screening.

- **Broaden access:** Provide screening options in resource-limited settings.

- **Promote early detection:** Identify cancer at earlier stages, improving the chances of successful treatment.

This thesis will delve into the potential of automatic detection techniques for cervical cancer screening. Key research questions include:

1. What are the challenges and limitations of automatic cervical cancer detection?

2. How can automatic detection be effectively integrated into existing healthcare systems?

Through these explorations, this thesis aims to contribute to the development of improved, accessible, and efficient methods for cervical cancer detection.

The structure of this thesis is as follows:

- Chapter One: provides a medical background on cervical cancer, exploring its causes, risk factors, and traditional screening methods.

- Chapter Two: outlines the methodology, focusing on the image processing techniques used for automatic detection.

- Chapter Three: discusses the hardware and software requirements essential for implementing these methods, examining the technologies that support efficient and accessible screening solutions.

Chapter1: Medical introduction of cervical cancer

Introduction:

Cervical cancer, a malignant tumor originating in the cells of the cervix, affects this narrow, lower portion of the uterus situated at the top of the vagina. Its development is driven by genetic mutations in normal cells, causing uncontrolled growth and tumor formation. The primary culprit behind cervical cancer is persistent infection with high-risk strains of the human papillomavirus (HPV), a sexually transmitted virus.

The cervix plays a vital role in women's reproductive health, especially during childbirth. It dilates to allow the passage of a baby from the uterus to the vagina. However, this crucial organ is susceptible to cellular changes that can progress to cancer, particularly when infected with persistent high-risk HPV.

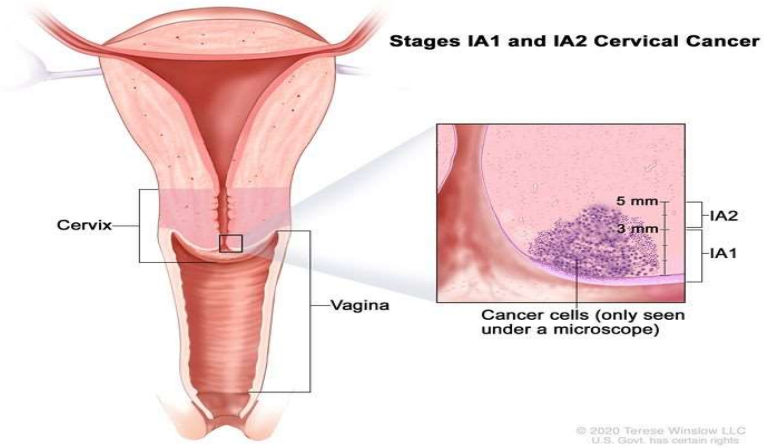


Figure 1:cervical cancer (Early detection)

Cervical cancer is confined solely to the cervix, the lowermost part of the uterus.

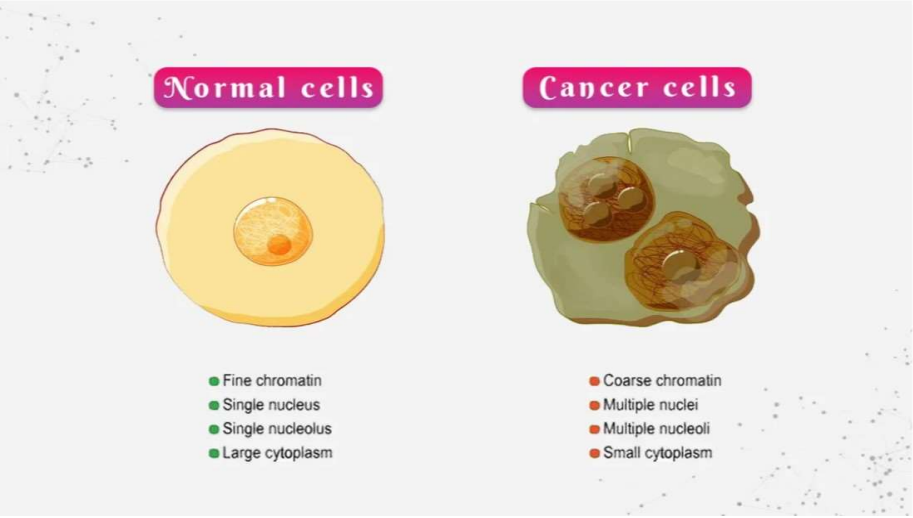


Figure 2:normal cells and cancer cells

1. Methods of diagnostic:

Traditional Methods:

- **Pap Smear:** While still widely used, the Pap smear's limited sensitivity and specificity require interpretation by trained cytologists.[1]
- **HPV Testing:** Detecting HPV infection alone doesn't distinguish between high-risk and low-risk strains, though combining it with Pap smears improves accuracy.[2]

Advanced Techniques:

- **Liquid-Based Cytology (LBC):** This method improves sample preparation and visualization, leading to better accuracy than conventional Pap smears.[3]
- **HPV Genotyping:** Identifying specific high-risk HPV strains associated with cervical cancer can guide treatment decisions.[4]
- **Primary HPV Screening:** More sensitive than Pap smears for detecting high-risk HPV infection, this method is recommended as the primary screening method by some guidelines.[5]

- **Automated Cervical Cancer Screening:** AI-powered algorithms are being developed to analyze Pap smear and HPV test results, improving accuracy and efficiency.[6]

Emerging Technologies:

- **Liquid Biopsy:** Detecting circulating tumor DNA in blood offers a non-invasive method for early detection, though still under research and development.[7]
- **Optical Imaging Techniques:** Techniques like colposcopy and fluorescence spec-troscopy can visualize cervical abnormalities, potentially improving accuracy and reducing unnecessary biopsies.[8]
- **Molecular Biomarkers:** Identifying specific molecular changes in cervical cells may aid in early detection and risk assessment, with ongoing research to identify and validate reliable biomarkers.[9]

Challenges and Future Directions:

- **Improving Accuracy and Specificity:** Reducing false-positive and false-negative results is crucial for effective screening.
- **Optimizing Screening Strategies:** Tailoring screening intervals and methods based on individual risk factors is important.
- **Integration of New Technologies:** Implementing advanced technologies into clinical practice requires further validation and cost-effectiveness analysis.

2. Current Limitations of Automated Cervical Cancer Detection

1. **Accuracy and False Positives/Negatives**
    - **Issue**: Automated systems can still produce false positives (indicating cancer when there is none) and false negatives (missing cancer cases). This can lead to unnecessary anxiety, additional tests, or missed diagnoses.

- **Details**: The sensitivity and specificity of automated systems may not always match the performance of experienced cytologists. False positives can result in overtreatment, while false negatives may miss early-stage cancers.

1. **Data Quality and Variability**
    - **Issue**: Automated detection systems rely heavily on the quality of the input data, which can vary significantly due to sample preparation, staining techniques, and image quality.
    - **Details**: Variability in sample quality and preparation can affect the consistency of automated results. Poor-quality images or improperly prepared samples may lead to inaccurate readings.

2. **Generalization and Adaptability**
    - **Issue**: Automated systems may struggle to generalize across different populations, healthcare settings, and technological platforms.
    - **Details**: Models trained on specific datasets might not perform equally well when applied to diverse populations or different clinical environments. This can limit the system's adaptability to varying demographics and regional practices.

3. **Integration with Clinical Workflow**
    - **Issue**: Integrating automated systems into existing clinical workflows can be challenging.
    - **Details**: There may be practical challenges in incorporating automated detection tools into routine screening processes, including the need for additional training for healthcare professionals and adjustments to workflow procedures.

4. **Regulatory and Validation Requirements**
    - **Issue**: Meeting regulatory standards and undergoing rigorous validation processes can be time-consuming and complex.

- **Details**: Automated systems must undergo extensive validation and approval processes to ensure they meet regulatory standards for clinical use. This can be a barrier to the widespread adoption of new technologies.

5. **Interpretation of Results**
   - **Issue**: Automated systems may provide results that require further interpretation by medical professionals.
   - **Details**: While automation can enhance efficiency, the results still need to be interpreted by trained healthcare providers. The effectiveness of the system depends on the integration of its results into clinical decision-making.

6. **Technological Limitations**
   - **Issue**: Current algorithms and technologies may have limitations in processing and analyzing complex patterns in cervical cells.
   - **Details**: The ability of automated systems to detect subtle cellular changes or complex patterns associated with early-stage cervical cancer is still evolving. Improvements in image analysis and machine learning algorithms are needed to enhance performance.

7. **Cost and Accessibility**
   - **Issue**: The cost of implementing advanced automated systems can be high, affecting their accessibility in resource-limited settings.
   - **Details**: High costs associated with advanced technologies may limit their availability, particularly in low-resource or underserved regions. This can impact the equitable distribution of screening technologies.

3. Advancements in Automatic Cervical Cancer Detection (2013-2024)

From 2013 to 2024, automatic detection of cervical cancer was a developing field. Machine learning and traditional image analysis techniques were used to develop models that could accurately detect cervical cancer cells in Pap smear images. These models had the potential to improve the accuracy and efficiency of cervical cancer screening and diagnosis. However, the accuracy, sensitivity, and specificity of these models were lower than those of models developed in recent years.

Years	method	Authors	notes
2013	Ensemble of decision trees	M.R. Islam et al [10]	Ensemble learning combines the strengths of multiple decision trees
2014	Rule-based system with expert knowledge	S.M. Islam, et al [11]	Expert knowledge is used to develop rules for classifying Pap smear images
2015	Support vector machines with handcrafted features	A.S. Al-Fahoum, et al [12]	Handcrafted features are designed specifically for cervical cancer detection
2016	Convolutional neural network with transfer learning	S.S. Kumar, et al [13]	Transfer learning from pre-trained models improves performance on smaller datasets
2017	Hybrid approach with support vector machines and texture analysis	M.R. Islam, et al [14]	Combines machine learning with traditional image analysis techniques

Table 1: state of the art (2013-2017)

4. Cervical Cancer Type:

1. **Squamous cell carcinoma:** Most common type (80-90%), arising from the exocervix

- **Adenocarcinoma:** This type of cervical cancer originates from the glandular cells lining the endocervical canal, the inner portion of the cervix connecting to the uterus. It accounts for a smaller percentage (10-20%) of cervical cancers compared to squamous cell carcinoma. In addition to the two main types, other less common forms of cervical cancer exist:

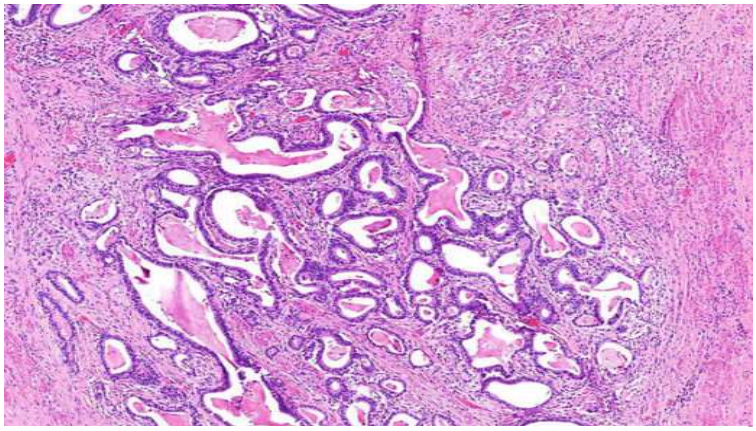


Figure 3:Adenocarcinoma

- **Adenosquamous carcinoma:** This type exhibits characteristics of both squamous cell carcinoma and adenocarcinoma.

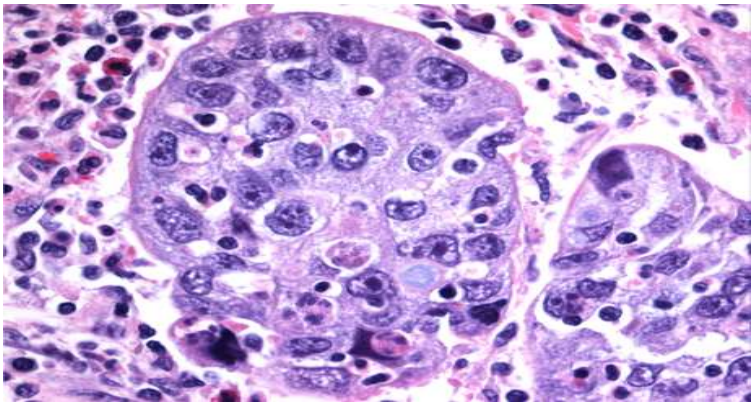


Figure 4:A microscopic view of adenosquamous carcinoma of the cervix

2. **Small cell carcinoma:** This aggressive neuroendocrine cancer can occur in the cervix.

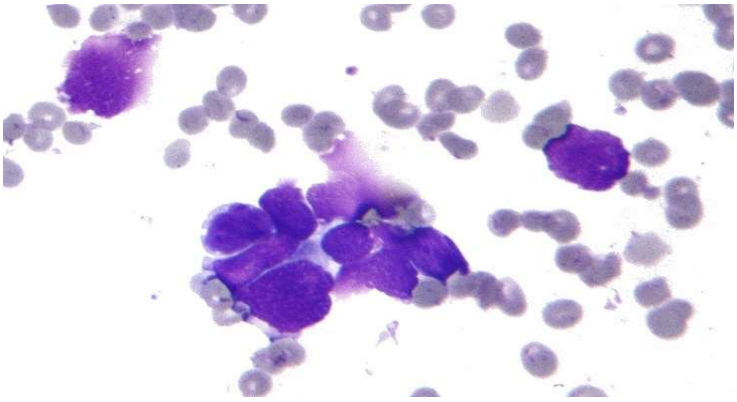


Figure 5: Small cell carcinoma is an aggressive form of cancer Clear cell adenocarcinoma

3. **Clear cell adenocarcinoma:** This rare type develops from glandular cells.

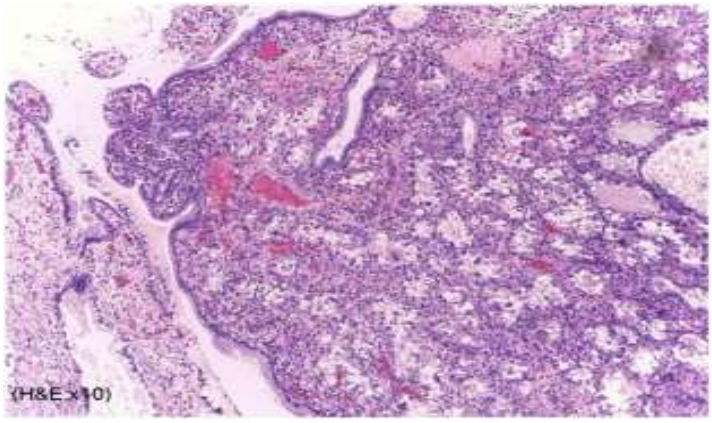


Figure 6:Clear cell adenocarcinoma

1. **Cervical sarcoma:** This form arises from the cervix's connective tissues. It's crucial to remember that cervical cancer is highly preventable. Vaccination against HPV, the primary risk factor, and regular screening with Pap and HPV tests are essential. Early detection and treatment significantly improve the chances of a successful outcome.

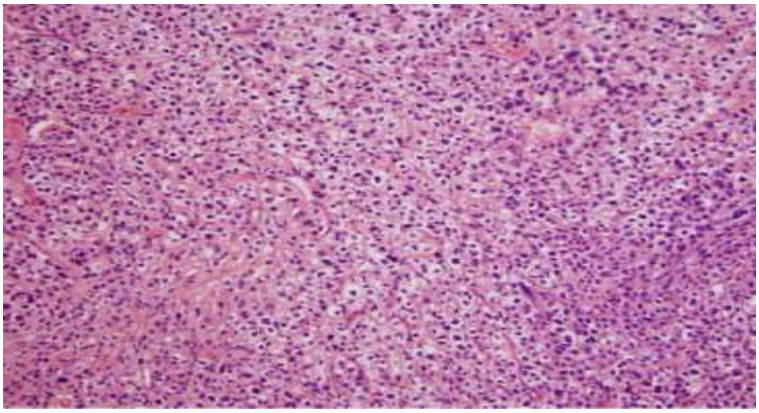


Figure 7: Cervical sarcoma

5. The life cycle of cervical cancer:

Cervical cancer, unlike some rapidly progressing cancers, develops gradually over years, making early detection and prevention crucial. The primary cause is HPV, which can cause precancerous changes in cervical cells. These changes, classified as CIN, can progress to invasive cancer if left untreated. Regular Pap tests and HPV tests can identify precancerous changes before they turn cancerous, allowing for effective prevention and early intervention.

6. Symptoms:

Early-stage cervical cancer often presents with no noticeable symptoms, emphasizing the critical role of regular screenings. Pap smears detect abnormal cervical cells, while HPV tests identify the presence of high-risk HPV strains, both crucial for early detection.

Symptoms of cervical cancer may include:

- Abnormal vaginal bleeding
- Pelvic pain
- Pain during intercourse
- Changes in urinary or bowel habits

Timely diagnosis and intervention significantly improve the chances of successful treatment.

7. Incubation:

Unlike many cancers, cervical cancer's early stages often lack noticeable symptoms, highlighting the importance of regular screenings. However, a well-defined period exists between initial HPV infection and the development of invasive cancer, known as the pre-cancerous phase or latency period.

- **HPV Infection:**
  Exposure to a high-risk HPV strain marks the starting point.
- **Precancerous Changes:**
  If the immune system fails to clear the HPV infection, it can trigger abnormal changes in cervical cells. This process can take months or even years.
- **Development Timeline:**
  The pre-cancerous phase progresses at a variable pace. In some women, these changes may take 10-15 years or longer to develop from mild dysplasia (CIN 1) to a severe stage (CIN 3) with a high risk of progressing to cancer.
  Not Inevitable:
  It's crucial to remember that not all HPV infections or precancerous changes lead to cancer. The body's immune system can often clear the virus and prevent further progression.
- **Early Detection is Key:**
  The slow progression of cervical cancer offers a significant advantage. Regular screening with Pap tests and HPV tests can detect precancerous changes before they turn cancerous.Early intervention through treatment of these precancerous lesions is highly successful in preventing invasive cervical cancer.

- **Analogy:**

  Instead of a fixed incubation period like a typical illness, think of cervical cancer development as a slow-burning fuse. Regular screening helps identify and extinguish the fuse before it reaches the explosive stage.

8. Reasons:

Several factors can increase the risk of developing cervical cancer, including:

- **Smoking:** Smoking weakens the immune system and damages cervical cells, making them more susceptible to HPV infection and cancer development.
- **Weakened Immune System:** Individuals with weakened immune systems, such as those with HIV/AIDS or undergoing immunosuppressive therapy, are at higher risk.
- **Long-Term Use of Oral Contraceptives:** While the exact mechanism is unclear, long-term use of oral contraceptives may slightly increase the risk of cervical cancer.
- **Family History of Cervical Cancer:** Having a family history of cervical cancer can indicate a genetic predisposition.

HPV Vaccination: A Powerful Tool for Prevention

Vaccination against HPV is a crucial preventive measure, particularly for young individuals. It significantly reduces the risk of infection with high-risk HPV strains, the primary cause of cervical cancer. Vaccination is most effective when administered before exposure to HPV, making it crucial to vaccinate adolescents before they become sexually active. By understanding and addressing these risk factors and prioritizing HPV vaccination, we can significantly reduce the burden of cervical cancer.

9. Diagnostic:

Screening plays a vital role in detecting precancerous cells before they develop into invasive cervical cancer. This is possible due to the slow progression of the disease, allowing for effective intervention during the precancerous stage. The most widely used screening tests for cervical cancer include:

1. Pap Test (Pap Smear):

This test involves collecting a sample of cells from the cervix using a brush or spatula.

These cells are then examined under a microscope for any abnormalities. The Pap test is a reliable and effective screening tool, with a long history of success in preventing cervical cancer.

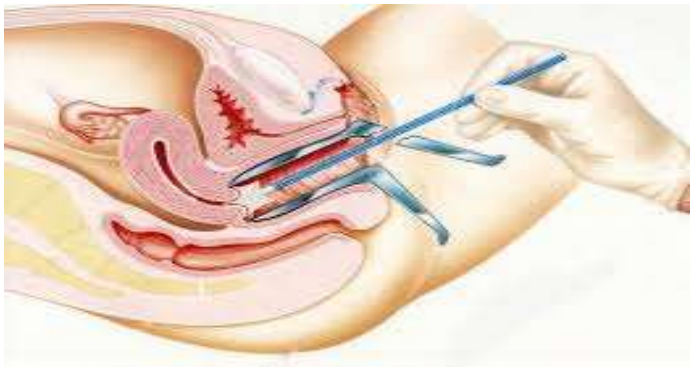


Figure 8:pap test (pap smear)

2. HPV Test:

This test directly detects the presence of HPV, the primary cause of cervical cancer. It is a highly sensitive test that can identify women at increased risk of developing cervical cancer.

Diagnosis: Confirming Cancer and Determining Stage

If a screening test shows abnormal results, further tests may be needed to confirm the presence of cancer and determine its stage (extent). This information is crucial for tailoring the most effective treatment plan.

Additional Tests:

Colposcopy: This procedure uses a special microscope to magnify the cervix for a closer examination. During a colposcopy, a healthcare professional may also take a tissue sample (biopsy) for further analysis.

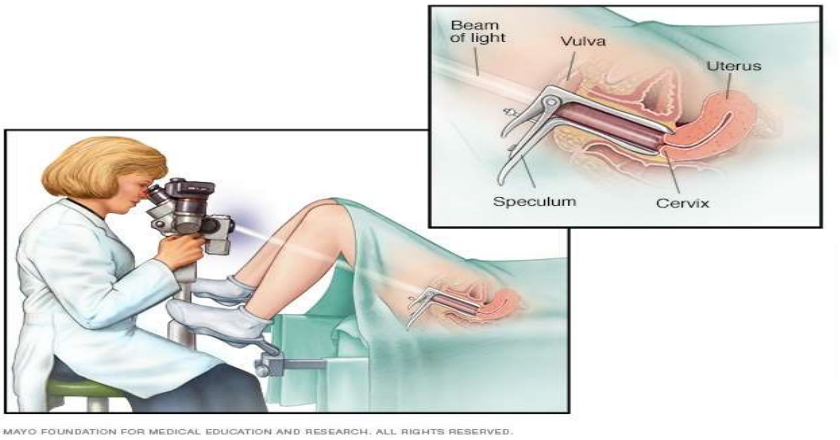


Figure 9: Colposcopy

2. **Biopsy:**

If further confirmation is needed, a biopsy may be performed. This involves taking a small sample of tissue from the cervix for examination under a microscope to confirm the presence of cancer cells.

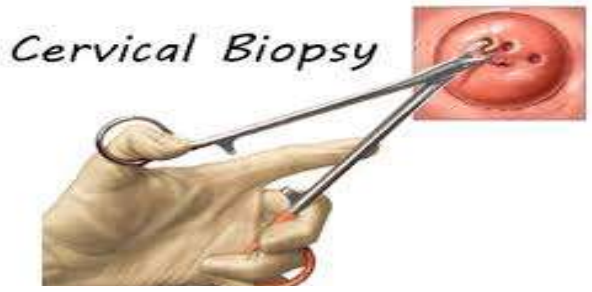


Figure 10: Cervical biopsy

4. Imaging Tests:

Imaging tests, such as MRI or CT scans, may be used to determine the stage of cancer and whether it has spread to other parts of the body. This information is crucial for guiding treatment decisions.

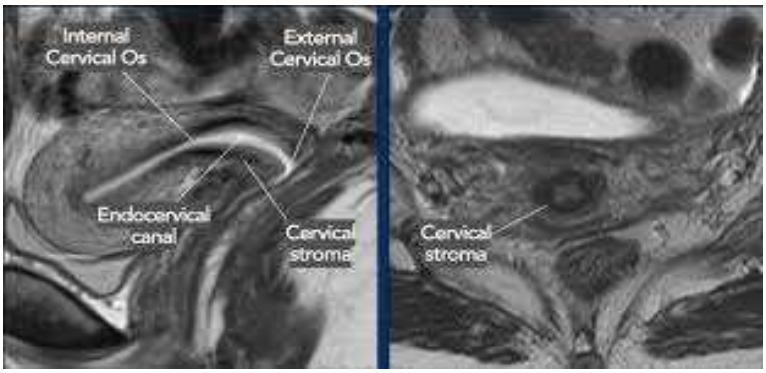


Figure 11: Radiology assistant

- **Importance of Early Detection:**

It's important to remember that an abnormal screening test result doesn't necessarily mean you have cancer. Most abnormal results are caused by precancerous changes that can be effectively treated. Early detection and treatment of cervical cancer are highly successful, significantly improving the chances of a cure.

- **Precautions for Prevention:**

Here are some key precautions you can take to reduce your risk of cervical cancer:

- **Vaccination:**

  HPV Vaccination: This is the single most effective way to prevent cervical cancer. The HPV vaccine protects against the strains of the human papillomavirus (HPV) that most commonly cause cervical cancer. The Centers for Disease Control and Prevention (CDC) recommends HPV vaccination for girls and boys starting at ages 11-12 [CDC].

- **Screening:**

  Regular Pap Tests and HPV Tests: These screening tests can detect precancerous

changes in the cervix before they turn into cancer. The recommended screening schedule may vary depending on your age and other factors.

- **Healthy Lifestyle Choices:**
  - **Don't Smoke:** Smoking weakens the immune system and can increase your risk of cervical cancer.
  - **Maintain a Healthy Weight:** Obesity is a risk factor for several cancers, including cervical cancer.
  - **Eat a Balanced Diet:** A diet rich in fruits, vegetables, and whole grains may help reduce your risk of cervical cancer.
- **Other Considerations:**
  - **Limiting Sexual Partners**: While not a foolproof method, reducing the number of sexual partners can lower your risk of HPV exposure.
  - **Condom Use:** Condoms can help prevent the transmission of HPV, although they are not completely effective.

- **Early Detection and Treatment:**

Regular screening and follow-up with your doctor are crucial for early detection and treatment of precancerous cervical lesions. Early intervention is highly successful in preventing the development of invasive cervical cancer. By following these precautions and prioritizing early detection, you can significantly reduce your risk of developing cervical cancer.

10. automatic diagnosis:

While significant progress has been made in cervical cancer screening and diagnosis, a fully automated system for diagnosis is not yet available. Here's a breakdown of the current process and the role automation plays:

- **Current Cervical Cancer Diagnosis:**
  - **Screening Tests:** Pap tests and HPV tests are the primary tools used to detect precancerous cells in the cervix. These tests are not diagnostic on their own, but abnormal results indicate a need for further investigation.
  - **Colposcopy and Biopsy:** If a screening test shows abnormalities, a colposcopy is performed. During this procedure, the cervix is magnified for a closer look, and a tissue sample (biopsy) may be taken. The biopsy is then examined under a microscope by a pathologist to confirm the presence or absence of cancer cells.
- **Role of Automation:**

Assisted Screening: Machine learning algorithms are being explored to assist

pathologists in analyzing Pap smears. These algorithms can help identify potentially abnormal cells, but a human pathologist always makes the final diagnosis.

Streamlining Workflow: Automation can play a role in tasks like managing test results, scheduling follow-up appointments, and generating reports. This can improve efficiency and communication within the healthcare system.

- **Limitations of Automation:**

Accuracy Concerns: While machine learning shows promise, it cannot fully replace the expertise of a pathologist in interpreting complex cellular changes. There's a risk of misdiagnosis with over-reliance on automation.

Ethical Considerations: Automated systems raise ethical concerns around bias and transparency. Algorithms trained on existing data may perpetuate existing disparities in healthcare access.

- **Future of Automation:**

Research on automated cervical cancer diagnosis is ongoing. The goal is to develop tools that can support pathologists, improve accuracy, and potentially make screening more accessible in resource-limited settings. However, complete automation for diagnosis is likely still some time away.

- **Key Points:**
  - Current cervical cancer diagnosis relies on a combination of screening tests, colposcopy, biopsy analysis by pathologists, and human expertise.
  - Automation is being explored to assist with screening and streamline workflow, but it doesn't replace human judgment in diagnosis.
  - Ethical considerations and accuracy concerns are important aspects to address in developing automated systems.

11. Treatment:

The treatment for cervical cancer depends on several factors, including the stage of the cancer (how advanced it is), the size and location of the tumor, and your overall health. Here's a breakdown of the common treatment options:

1. **Surgery:**

- **Cone Biopsy:** This procedure removes abnormal tissue from the cervix and may be used for early-stage cancer.
- **Hysterectomy:** This surgery involves removing the uterus, cervix, and sometimes surrounding tissues like lymph nodes. There are different types of hysterectomies depending on the extent of tissue removal required.

- **Radical Trachelectomy:** This surgery removes the cervix, upper part of the vagina, and surrounding lymph nodes, while preserving the uterus. It may be an option for young women who want to preserve their fertility.

2. Radiation Therapy :

Radiation therapy uses high-energy rays to kill cancer cells. It can be delivered externally, through a machine, or internally, by placing radioactive implants near the tumor.

Radiation therapy may be used before surgery to shrink the tumor or after surgery to destroy any remaining cancer cells.

1) Chemotherapy:

Chemotherapy uses powerful drugs to kill cancer cells throughout the body. It's often used in combination with radiation therapy for more advanced stages of cervical cancer.

2) Targeted Therapy:

Targeted therapy drugs focus on specific weaknesses in cancer cells. These drugs may be an option for certain types of cervical cancer, especially those with specific genetic mutations.

3) Immunotherapy:

Immunotherapy helps your body's immune system fight cancer cells. It's a relatively new treatment option for cervical cancer, but research is ongoing. Choosing the Right

12. Conclusion:

This chapter offered a comprehensive medical introduction to cervical cancer, highlighting its significant impact on global health. We explored various aspects of the disease, including symptoms, complications, and treatment options. Additionally, we discussed important advancements in the field of automated cervical cancer diagnosis.

The next chapter will delve deeper into the technical aspects of image segmentation techniques, exploring their potential to further enhance cervical cancer diagnosis.

By leveraging these technologies, we aim to gain a more comprehensive understanding and contribute to ongoing efforts in combating this global health challenge.

Chapter 2: Methodology

Introduction:

Cervical cancer, a significant public health issue, demands early detection for better treatment outcomes. Current detection methods, hampered by limitations in accuracy and efficiency, can be enhanced by the potential of machine learning for automated detection.

Image segmentation, essential for identifying and segmenting cell nuclei in cervical smear images, is effectively accomplished using the K-means algorithm. Evaluation of segmentation performance through Jaccard and Dice similarity indices ensures the reliability of the automated detection system.

By combining image segmentation and machine learning, it is possible to develop more accurate and efficient automated cervical cancer detection systems. These systems can analyze images, identify suspicious nuclei, and provide pre-diagnosis, enabling pathologists to prioritize critical cases.

This work investigates the use of the K-means algorithm for cell nuclei segmentation and evaluates its performance using Jaccard and Dice similarity indices. We aim to showcase the potential of machine learning for improving automated cervical cancer detection and contributing to the fight against this disease.

1. **Pap-Smear Database**

   The Pap-Smear database is a recent dataset developed collaboratively by Herlev University Hospital's Department of Pathology and the Department of Automation at the Technical University of Denmark. This dataset significantly expands upon an earlier version, which contained only 500 samples. While the feature set remains consistent, the output classes have been slightly modified, leading to increased overlap between classes in the new dataset (Martin, 2003). Both datasets are designed for research into automated classification systems.

2. **Data Collection Process**

   To create the database, skilled cytotechnicians at Herlev University Hospital utilized a microscope with a resolution of 0.201 μm/pixel to capture digital images of individual cells from a vast collection of raw glass slides. Each captured cell image was then manually classified into one of seven distinct cell types. For quality assurance, the classification process was independently

performed by two different cytotechnicians. Any image that failed to achieve consensus between the two classifiers was discarded.

3. **Dataset Distribution**

The dataset is composed of the following cell types:

Normal Cells:

Superficial squamous epithelial: 74 cells

Intermediate squamous epithelial: 70 cells

Columnar epithelial: 98 cells

Abnormal Cells:

Mild squamous non-keratinizing dysplasia: 182 cells

Moderate squamous non-keratinizing dysplasia: 146 cells

Severe squamous non-keratinizing dysplasia: 197 cells

Squamous cell carcinoma in situ intermediate: 150 cell

2.Definition of the method

Automatic detection of cervical cancer cells with a microscope and camera leverages the power of computer vision and machine learning to analyze microscopic images and identify cancerous cells. This innovative approach aims to revolutionize cervical cancer screening by automating the traditionally manual process of cell analysis and this is based on artificial intelligence, performed by trained cytologists.

Figure 12: Microscope

2.1 Method of automatic detection:

a) Cervical cancer detection steps:

- **Sample Collection:** Cervical cancer screening typically involves collecting samples via a Pap smear or HPV test. During a Pap smear, a speculum is used to expose the cervix, and a brush or spatula collects cells from its surface. These cells are then transferred to a glass slide or liquid preservative for analysis. For an HPV test, a brush or swab collects cells from the cervix, which are sent to a lab for HPV detection. If abnormalities are detected during screening, a colposcopy may be performed. This procedure involves using a magnifying instrument to examine the cervix in detail. A solution of acetic acid or iodine may be applied to highlight abnormal areas. If suspicious areas are identified, a biopsy may be taken using a punch biopsy or LEEP procedure. The tissue sample is then sent to a lab for examination under a microscope to confirm the diagnosis of cervical cancer. Sample collection for cervical cancer screening is generally a quick and painless procedure. Following the healthcare provider's instructions before and after the procedure is crucial.
- **Pretreatment of samples:** Pretreatment plays a crucial role in preparing samples collected for cervical cancer detection, ensuring accurate and reliable results. Common pretreatment steps include fixation, dehydration, clearing, embedding, and staining. Fixation preserves cell morphology, dehydration prevents bacterial growth, clearing removes interfering substances, embedding provides structural support, and staining enhances contrast and visibility. The choice of methods depends on the sample type and analysis requirements. Proper handling, storage, and quality control measures are essential to maintain sample integrity and prevent contamination.

- **Digital imaging:** has revolutionized cervical cancer detection, offering invaluable tools for diagnosis and treatment planning. Various imaging modalities, each with its unique strengths, are employed to provide a comprehensive picture of the disease. Colposcopy, a non-invasive procedure, uses a magnifying instrument to visualize the cervix in detail, allowing for the identification of suspicious areas. Pap smears and HPV tests collect cells or detect the virus responsible for most cervical cancers, respectively, enabling early detection of precancerous and cancerous cells.

  Biopsies, minimally invasive procedures, remove tissue samples for definitive diagnosis under a microscope. Imaging tests like ultrasound, CT scans, and MRI provide information about the stage and spread of the cancer, aiding in treatment planning and monitoring. Digital imaging offers numerous advantages, including improved accuracy and objectivity in diagnosis, enhanced visualization of cervical abnormalities, faster and more efficient workflow, and easier data sharing and collaboration. This technology empowers healthcare providers with a comprehensive understanding of the disease, enabling them to provide optimal care for their patients.

- **Image processing:** has emerged as a transformative tool in cervical cancer detection, significantly enhancing the accuracy and efficiency of diagnosis. This technology involves a series of techniques applied to digital images to extract meaningful information and improve their diagnostic value.

  Key image processing techniques include image enhancement, segmentation, feature extraction, and classification. Image enhancement improves image quality and visibility of subtle details.

  Segmentation isolates regions of interest, such as the cervix and potential lesions, from the background. Feature extraction quantifies characteristics like texture, shape, and color to characterize lesions and differentiate them from normal tissue. Classification algorithms use these features to categorize lesions as benign or malignant. Image processing offers numerous benefits, including improved diagnostic accuracy, increased efficiency, and standardized analysis. Automated analysis assists pathologists in identifying subtle abnormalities, reduces workload for healthcare professionals, and provides objective and consistent results. Applications in cervical cancer detection include automated Pap smear analysis, colposcopy image analysis, and HPV test image analysis. These applications

improve the detection and management of this potentially life-threatening disease, ultimately contributing to improved patient outcomes.

b) Prediagnostic of cervical cancer:

- **Segmentation image:** plays a pivotal role in image processing for cervical cancer detection. It involves identifying and isolating regions of interest, such as the cervix and potential lesions, from the background. This process is crucial for accurate diagnosis and treatment planning.

  Various segmentation techniques are employed, each with its strengths and limitations. Thresholding classifies pixels based on intensity values, separating the foreground from the background. Edge detection identifies edges and boundaries based on intensity changes.

  Region growing groups pixels with similar characteristics to form regions. Machine learning algorithms can be trained to segment images based on labeled data or image features.

  Segmentation is essential for accurate lesion identification, quantitative analysis, and feature extraction. It helps isolate suspicious areas for further analysis and characterization, enables measurement of lesion size and extent, and facilitates the extraction of relevant features for classification and diagnosis.

  Applications in cervical cancer detection include automated Pap smear analysis, colposcopy image analysis, and HPV test image analysis. These applications improve the detection and management of this potentially life-threatening disease, ultimately contributing to improved patient outcomes.

- **K-means:**

K-Means is a powerful algorithm that excels at grouping individuals into clusters without any prior knowledge or assumptions. Unlike some machine learning algorithms, it cannot predict specific outcomes, as it falls under the category of unsupervised methods.

Unsupervised Nature:

- K-Means does not require labeled data, making it suitable for situations where data is unlabeled or true labels are unavailable.
- It relies solely on the inherent similarities between individuals to group them into clusters.

Grouping Mechanism:

- The algorithm aims to partition individuals into a predefined number of clusters (k).
- Each cluster is represented by a centroid, which is the average of all individuals belonging to that cluster.
- Individuals are assigned to clusters based on their proximity to the centroids, using a distance metric like Euclidean distance.

Iterative Process:

- K-Means follows an iterative approach:
- It starts with initial centroids, either chosen randomly or placed strategically.
- It then assigns each individual to the nearest centroid, forming initial clusters.
- The centroids are then recalculated as the mean of the individuals in each cluster.
- This process of assigning and recalculating continues until the centroids stabilize or a maximum number of iterations is reached.

Applications:

- K-Means finds applications in various domains, including:
- **Image Segmentation:** Grouping pixels with similar features to identify objects or regions of interest.
- **Customer Segmentation:** Grouping customers based on their purchase history or demographics to personalize marketing campaigns.
- **Anomaly Detection:** Identifying individuals who deviate significantly from the norm, potentially indicating fraud or system failures.

Advantages:

- **Simplicity:** Easy to understand and implement.
- **Efficiency:** Relatively fast and computationally efficient.
- **Scalability:** Can handle large datasets.

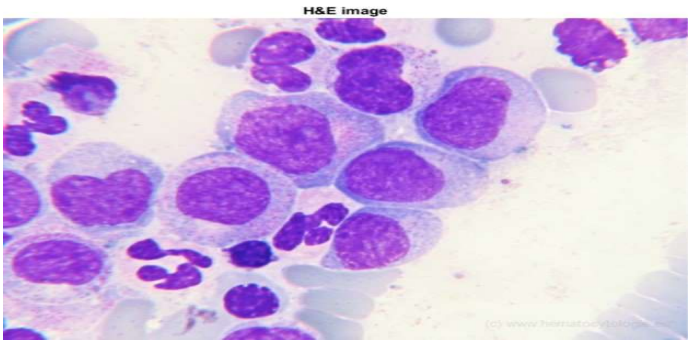
Disadvantages:

- **Predefined Clusters:** Requires pre-specifying the number of clusters, which can be challenging to determine.
- **Sensitive to Initialization:** The final clusters can be influenced by the initial centroid assignments.
- **Not Suitable for Complex Data:** May not be effective for segmenting images with high variability or complex features.

K-means steps:

1) **Read image:**

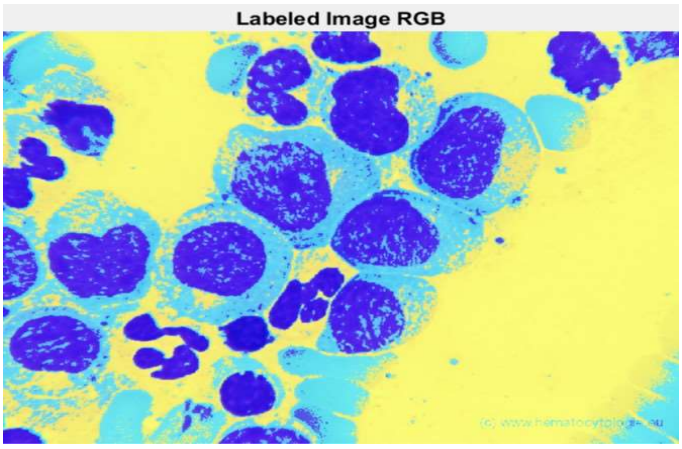
Load and visualize an H&E-stained tissue image. This staining technique allows pathologists to differentiate between tissue types based on their blue-purple and pink coloration.



Annex 1: Read image

2) **Classify Colors in RBG Color Space Using K-Means Clustering:**

We segmented the H&E image into three clusters using K-Means in the RGB color space. The resulting label image, overlaid on the original, incorrectly grouped white, light blue-purple, and light pink regions. This is due to the RGB space combining brightness and color, making lighter shades of different colors closer and harder to segment than darker shades of the same colors.



Annex 2: Classify Colors in RBG Color Space Using K-Means Clustering

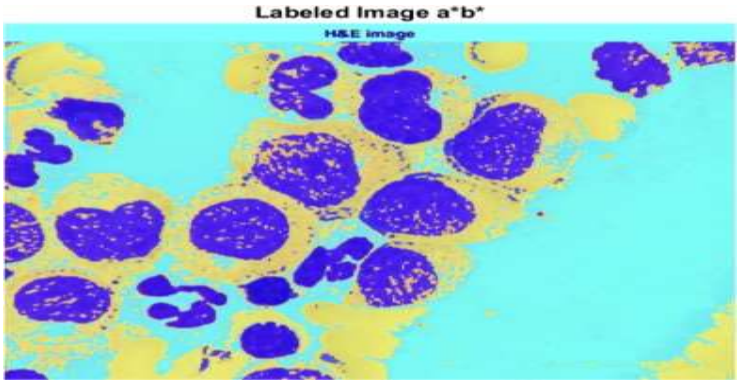
3) **Convert image from RGB color space to L*a*b color space:**

The L*a*b color space separates image luminosity and color, facilitating color-based segmentation independent of lightness. This space aligns better with human visual perception, distinguishing the distinct white, blue-purple, and pink regions in the image. Derived from CIE XYZ tristimulus values, L*a*b comprises the luminosity layer L*, the chromaticity layer a* for red-green, and the chromaticity layer b* for blue-yellow, with all color information residing in a* and b*. We will convert the image to Lab* using the rgb2lab function.

4) **Classify Colors in a*b* Space Using K-Means Clustering:**

To segment the image based solely on color, we'll extract the a* and b* channels from the Lab* representation, ensuring data type single for compatibility with imsegkmeans. This function will then segment the image into three clusters, repeating the process three times with different initial centroids to avoid local minima.

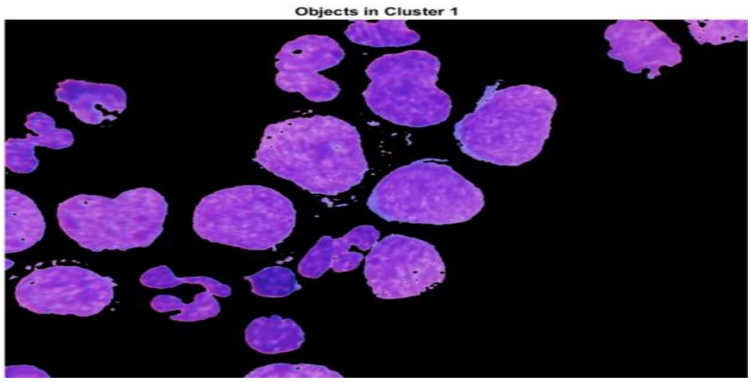
The label image, overlaid on the original, now demonstrably separates the white, blue-purple, and pink stained tissue regions with greater clarit



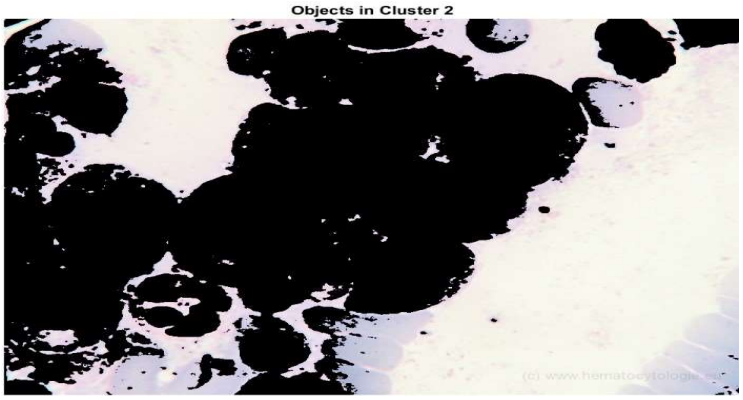
Annex 3: Classify Colors in a*b* Space Using K-Means Clustering

5) **Create Images that Segment H&E Image by Color:**

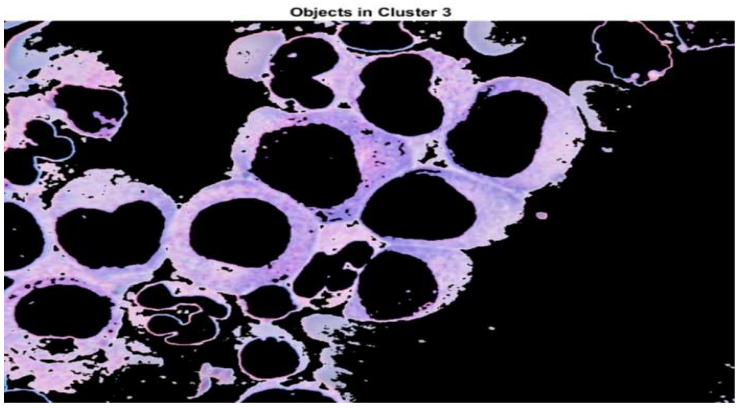
With the pixel labels, we can isolate objects in the original 1.png image based on their color, generating three distinct masked images



Annexe 5: Objects in cluster 1



Annexe 4: Objects in cluster 2

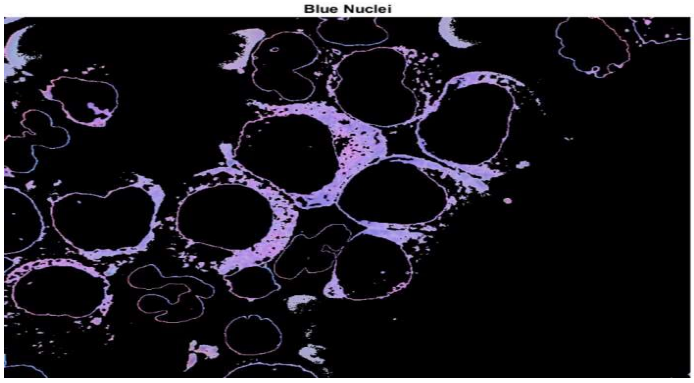


Annexe 6: Objects in cluster 3

6) Segment Nuclei:

Cluster 3 exclusively contains the blue objects, encompassing both dark and light shades. To separate these, we'll utilize the L* layer of the Lab* space, which represents brightness. Extracting the brightness values of this cluster and applying a global threshold with imbinarize yields a mask (idx_light_blue) that identifies the light blue pixels.

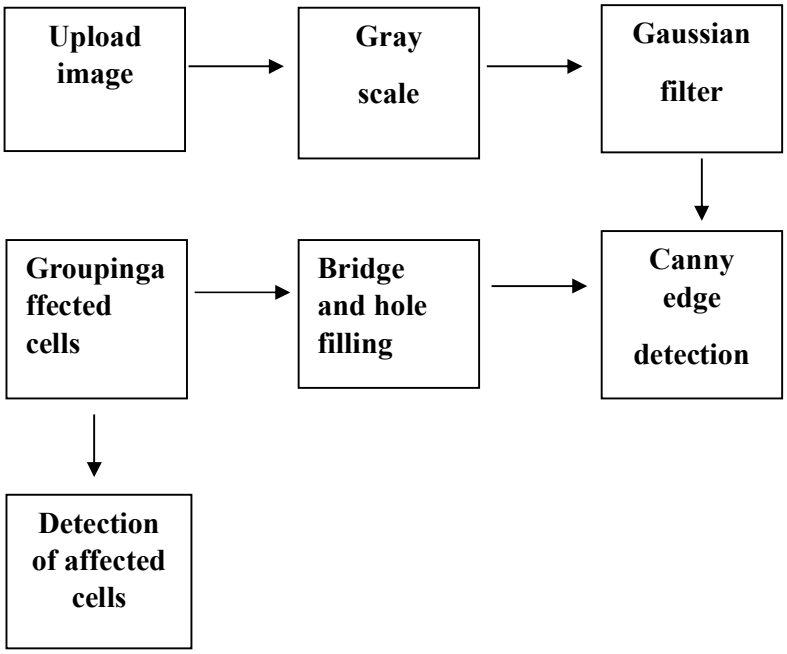
We'll begin by duplicating the mask of blue objects (mask3). Next, we'll remove the light blue pixels from this mask, ensuring that only the dark blue cell nuclei remain visible. Applying this refined mask to the original image will reveal solely the dark blue cell nuclei.[15]



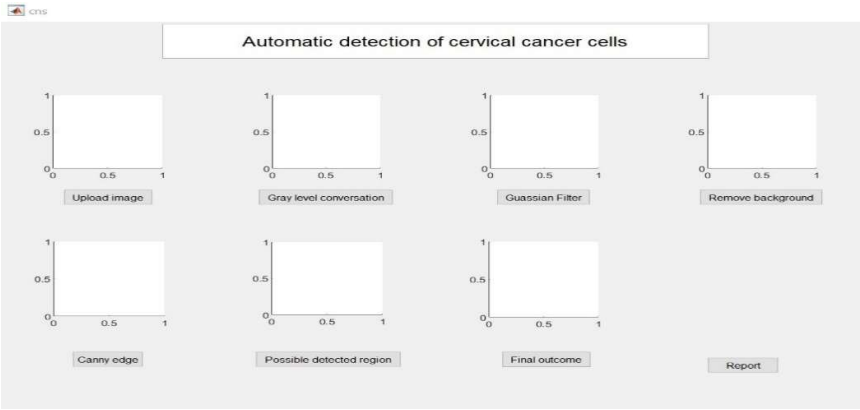
Annexe 7: Segment Nuclei

7) **Automatic detection:**

is the process of bringing a plan, method, or design to life, encompassing all steps required to get new software or hardware functioning correctly in its environment. This includes installation, configuration, testing, and making necessary adjustments. The term "deployment" is often used interchangeably. Effective implementation requires careful planning, resource allocation, stakeholder communication, risk management, and change management, ultimately leading to improved efficiency, better decision-making, increased customer satisfaction, and reduced costs and risks.



Plan 1: Methodology plan



Annexe 8: User interface

- **Uploading an image:**

Annexe 9: Upload image

- **Gray level conversation:**

The 3D RGB image undergoes a conversion to a 2D gray

Annexe 10:: Gray level conversation

- **Gaussian filter:**

In image processing, a Gaussian blur smooths an image by applying a Gaussian function. This widely used technique reduces image noise and detail, creating a smooth blur similar to viewing the image through a translucent screen. Unlike bokeh or out-of-focus effects, Gaussian blurring maintains a distinct visual appearance. In this project, the Gaussian filter is applied to reduce the gap between affected cells, effectively smoothing the image.

Annexe 11: Gaussian filter

- **Grouping affected cells:**

Adaptive thresholding is an image segmentation algorithm that effectively handles varying lighting conditions. Unlike basic thresholding, which uses a fixed value, adaptive thresholding dynamically adjusts the threshold based on local image characteristics. This allows for accurate segmentation even in images with uneven illumination. In this project, adaptive thresholding is used to retain affected cells while considering the maximum intensity values of the smoothed image as the background. This approach ensures accurate segmentation of the affected areas.

Annexe 12: Grouping affected cells

- **Edge technique:**

The Canny edge detection technique is employed to identify the sharp transitions between affected and non-affected cells. This technique effectively highlights the edges of these cells, allowing for clear differentiation between the two regions. By utilizing the Canny edge detector, we can accurately segment the affected areas from the healthy tissue.

Annexe 13: Edge technique

- **Extraction of holes:**

Affected cells exhibit large-sized holes, while non-affected cells display smaller holes. In instances where cells fail to generate holes, the bridge morphological function intervenes to create them. This ensures that all cells, regardless of their initial state, are accurately identified and segmented.

Annexe 14: Extraction of holes

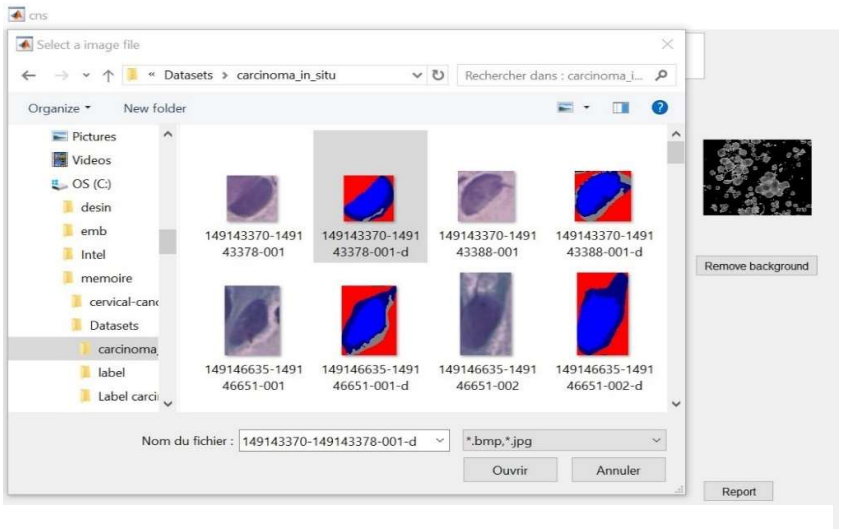
- **Extraction of affected cells:**

  The larger components, indicative of affected cells, are preserved through the effective application of morphological functions. This ensures that the segmentation process accurately identifies and retains these crucial regions for further analysis.

Annexe 15: Extraction of affected cells

- **Accuracy displaying in percentage:**

  We choose an image as a reference for comparing the cells, this image should be cancer cells



Annex 16: Detecting accuracy by using ground truth image for cervical cell.

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- **Jaccard and Dice Similarity: Measuring the Similarity Between Sets**

  Jaccard and Dice similarity are two metrics used to quantify the resemblance between two sets. They find extensive application in image segmentation, where they evaluate the performance of algorithms by comparing the predicted segmentation with the ground truth.

Jaccard Similarity

- **Formula:** Jaccard similarity is calculated as the ratio of the intersection of two sets to their union.

  Jaccard similarity = $|A \cap B| / |A \cup B|$ Range:0 to 1

  - **Interpretation:** A higher Jaccard similarity indicates a greater degree of overlap between two sets.
  - > 0.8: Perfect similarity between the sets.
  - < 0.8: No significant similarity (can be denoted as "NAN").
  - Otherwise: A degree of similarity between 0 and 1.

Dice Similarity

- **Formula:** Dice similarity is calculated as twice the intersection of two sets divided by the sum of their sizes.
- **Range:** Values also range from 0 to 1, with the same interpretation as Jaccard similarity.
- **Relationship:** Dice similarity is closely related to Jaccard similarity, with a simple mathematical relationship: Dice = 2 * Jaccard / (1 + Jaccard).

Choosing the Right Metric

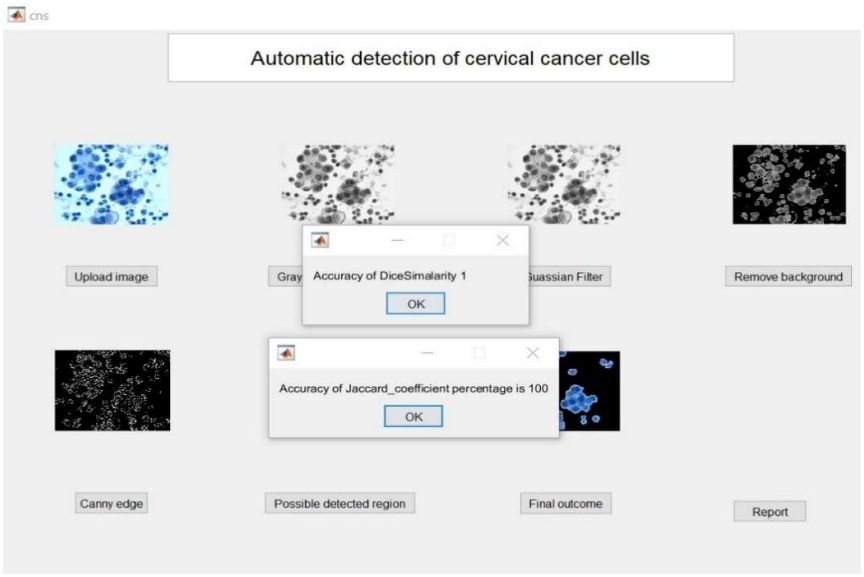
- **Jaccard:** More sensitive to differences in set sizes.
- **Dice:** Less sensitive to set size differences, making it more suitable for comparing segmentations with varying numbers of elements.

Applications

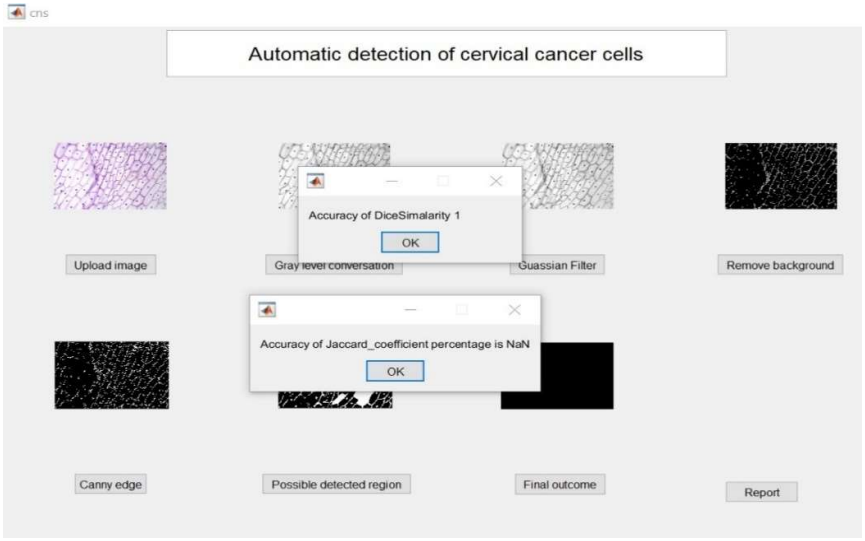
- **Image Segmentation:** Evaluating the performance of segmentation algorithms.
- **Information Retrieval:** Measuring the similarity between documents or search results.

- **Bioinformatics**: Comparing sets of genes or proteins.

Examples:

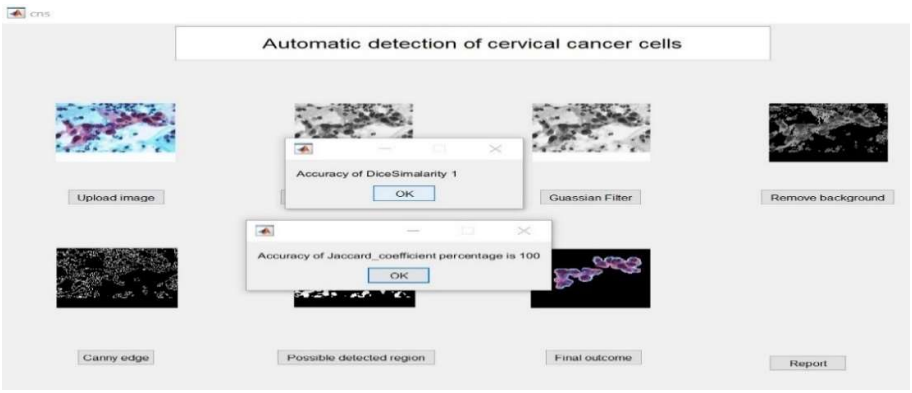


Annex 17: When Jaccard coefficient is 100 and Dice similarity is 1, then it is cancer.

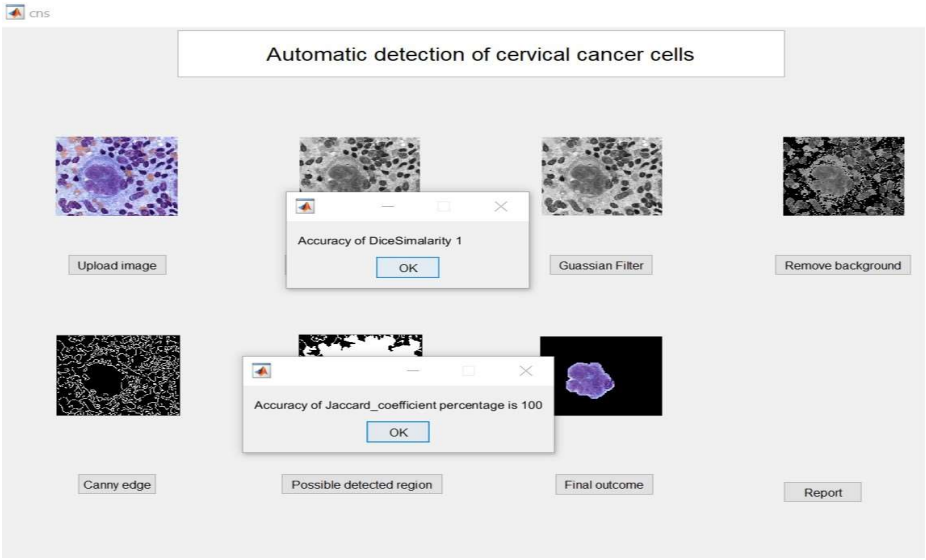


Annex 18: When Jaccard coefficient is NAN and Dice similarity is 1, then it is not cancer

Other examples about Jaccard coefficient and Dice similarity:



Annex 19: Jaccard coefficient is 100 and Dice similarity is 1, then it is cancer



Annex 20: Jaccard coefficient is 100 and Dice similarity is 1, then it is cancer

Annexes	Dice similarity	Jaccard coefficient	result
Annex 17	1	100	Cancer
Annex 18	1	NAN	Not cancer
Annex 19	1	1	Cancer
Annex 20	1	1	Cancer

Table 2: Dice similarity and Jaccard coefficient result

Quality assessment:

Evaluating the quality of segmentation is paramount in cervical cancer detection, as accurate segmentation directly impacts the reliability of subsequent analysis and diagnosis. Various metrics and techniques are employed to assess segmentation performance, ensuring the trustworthiness of the results. Common segmentation quality metrics include the Dice Similarity Coefficient (DSC), Jaccard Index (JI), sensitivity, specificity, precision, and accuracy. These metrics quantify the overlap between the segmented region and the ground truth, the proportion of correctly identified pixels, and the overall accuracy of the segmentation.

Visual inspection, quantitative analysis, and statistical analysis are employed to assess segmentation quality. Visual inspection compares the segmented image with the original image and ground truth to identify discrepancies. Quantitative analysis calculates metrics like DSC, JI, and accuracy to numerically assess performance. Statistical analysis compares segmentation results across different algorithms or datasets to evaluate their relative effectiveness.

Image quality, choice of segmentation algorithm, and parameter tuning influence segmentation quality. Noise, artifacts, and poor contrast in images can affect accuracy. Different algorithms have varying strengths and weaknesses, depending on image characteristics and task requirements. Optimizing algorithm parameters can significantly impact segmentation quality.

Quality assessment ensures reliable analysis, guides algorithm selection and optimization, and improves patient care. Accurate segmentation contributes to reliable feature extraction, classification, and diagnosis, ultimately leading to better patient outcomes.

8) **Future updates:**

Deep learning, a powerful subset of artificial intelligence, leverages artificial neural networks with multiple layers to learn from vast amounts of data. These networks mimic the human brain's structure and function, with interconnected nodes processing information and learning from experience. [16][17]

Key Features:

- **Multi-layered Architecture:** Deep learning models boast multiple hidden layers, enabling them to learn complex patterns and relationships within data.
- **Data-Driven Learning:** These models thrive on large datasets, identifying patterns and making accurate predictions.
- **Versatility:** Deep learning models can be adapted to various tasks, including image recognition, natural language processing, speech recognition, and predictive analytics.
- **Benefits:** High accuracy, automated feature extraction, and adaptability.
- **Challenges:** Computational requirements, interpretability, and data bias.

As deep learning technology continues to advance, we can expect even more groundbreaking applications and advancements in the field of artificial intelligence.[18][19]

3.Comparison between traditional and automatic detection methods:

Traditional cervical cancer detection methods, limited by subjectivity and accuracy, are being challenged by machine learning-based approaches that offer higher accuracy and automation, but require substantial data and resources. These methods hold promise for improving early detection and patient outcomes.

In this table, we present a simple comparison between traditional methods and machine learning methods:

features	Automatic detection Methods	Traditional methods
Subjectivity	Low	High
Accuracy	High	Moderate
Automation	High	low
Cost	High (initial development)	moderate
Availability	Limited availability	Widely available
Time	Minutes to hours	Several days to weeks

Table 3: comparison between traditional methods and machine learning based methods

4.General conclusion:

Cervical cancer, a major health concern for women, demands innovative solutions for early detection and effective treatment. Image processing offers a promising avenue for addressing this challenge, enabling more accurate diagnosis, personalized treatment, and ultimately improved patient outcomes. Data hubs, like the one presented, can connect various sources, facilitating comprehensive analysis and accurate AI-powered predictive models. Processing algorithms can identify subtle abnormalities in images, empowering early detection and improved patient outcomes. Machine learning can analyze patient data to predict individual responses to treatment, enabling personalized strategies. Addressing data bias and ensuring model interpretability are crucial for responsible and equitable healthcare. Continuous research and development in these fields, alongside integration with emerging technologies, hold immense potential for revolutionizing cervical cancer management, ultimately improving patient survival. This calls for collaborative efforts between researchers, clinicians, technologists, and AI experts to develop and implement these innovative solutions for a healthier future. This rephrased conclusion emphasizes the critical role of AI in revolutionizing cervical cancer management and improving patient lives, while also acknowledging the importance of data hubs, deep learning, machine learning, and collaborative efforts.

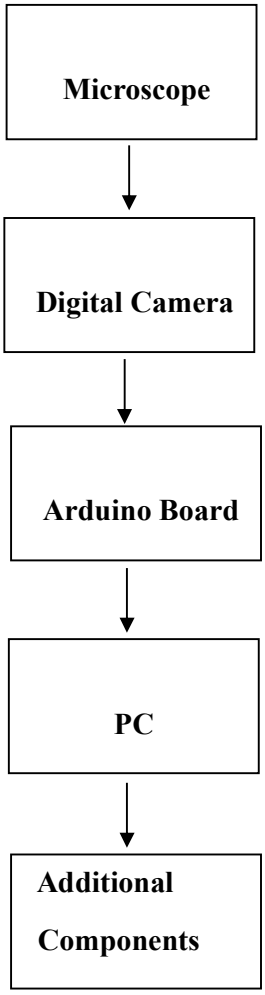
Chapiter 3: Hardware & Software: Powering Cervical Cancer Detection

Introduction:

Cervical cancer detection relies on a delicate balance between hardware and software. Hardware captures and analyzes images, while software provides the intelligence to identify cancerous cells. This chapter compares the strengths and limitations of both hardware and software in this context. We explore various hardware options like microscopes, cameras, and processing boards, and delve into the capabilities of software tools for image acquisition processing. Understanding this interplay is crucial for optimizing cervical cancer detection and improving patient outcomes.

1.Hardware Setup:

- **Microscope:** Choose a microscope with at least 400x magnification and a digital camera port or adapter. Consider options like a USB microscope or a traditional microscope with a C-mount adapter for connecting a digital camera.
- **Camera**: Select a high-resolution camera (at least 5 megapixels) with good color accuracy and sensitivity. Ensure it's compatible with your computer and microscope setup.
- **Arduino Board:** Choose an Arduino board with sufficient processing power and memory to handle image acquisition and communication with the computer. The Arduino Uno or Mega are suitable options.
- **PC:** Use a computer with sufficient processing power and memory to run MATLAB and perform image processing tasks. A minimum of 8GB RAM and a quad-core processor is recommended.
- **Additional Components:** You'll need cables (USB, HDMI, etc.), connectors, power supplies, and a suitable enclosure for the system.



3.Using the OV7670 Camera Module with Arduino:

The OV7670 is a low-cost camera module that can be used with Arduino to capture images and videos.

To use the camera:

A. Connect the camera module to the Arduino board using jumper wires.
B. Install the ArduCAM library, which provides functions for controlling the camera.
C. Upload an example code that demonstrates how to use the camera.
D. Open the serial monitor to view the camera output.

1. **Components required:**
    - Arduino UNO
    - OV7670 Camera Module
    - Resistors (10k, 4.7k)
    - Jumpers
2. **Software required:**
    - Arduino IDE

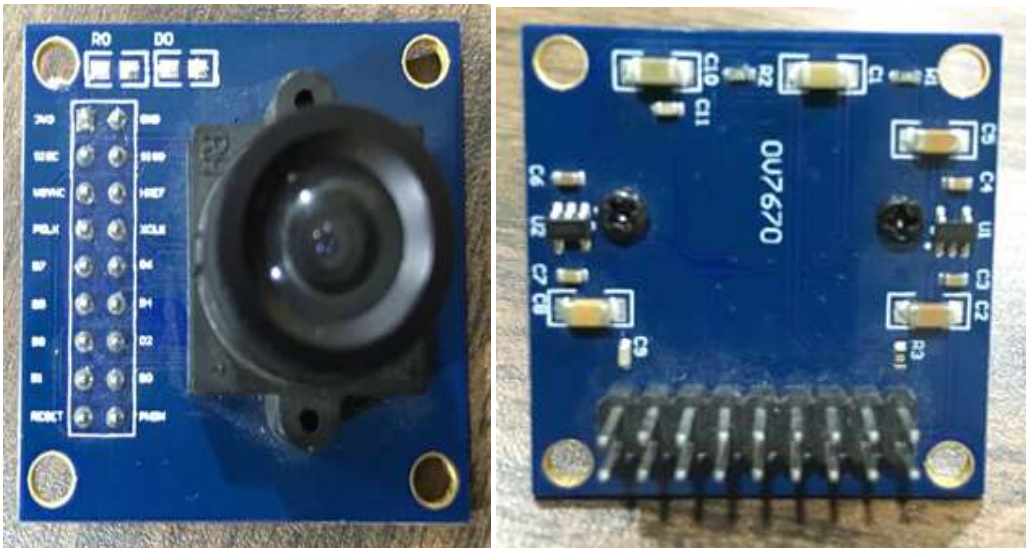


Figure 24: Camera Module OV7670

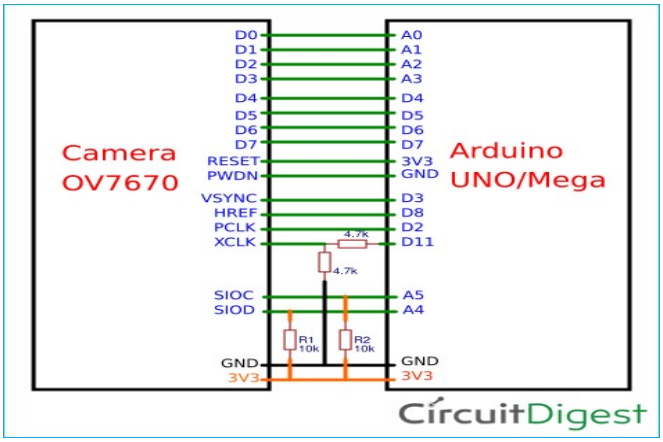
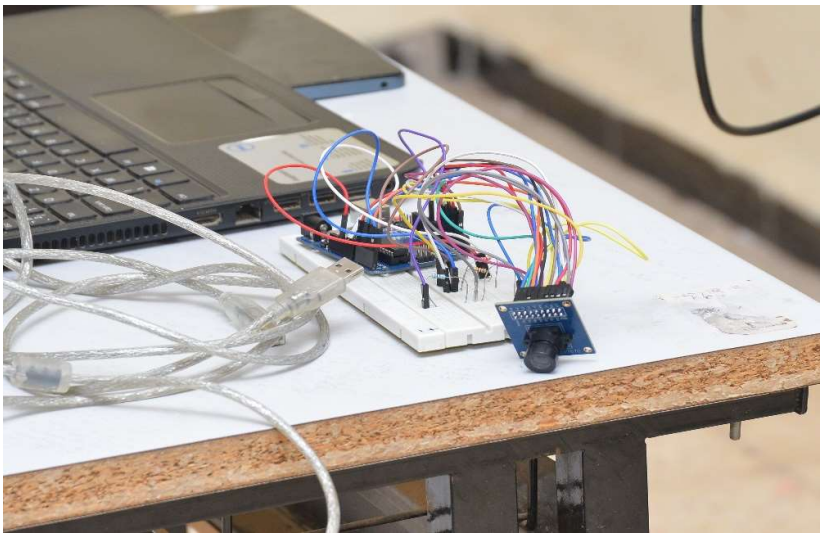


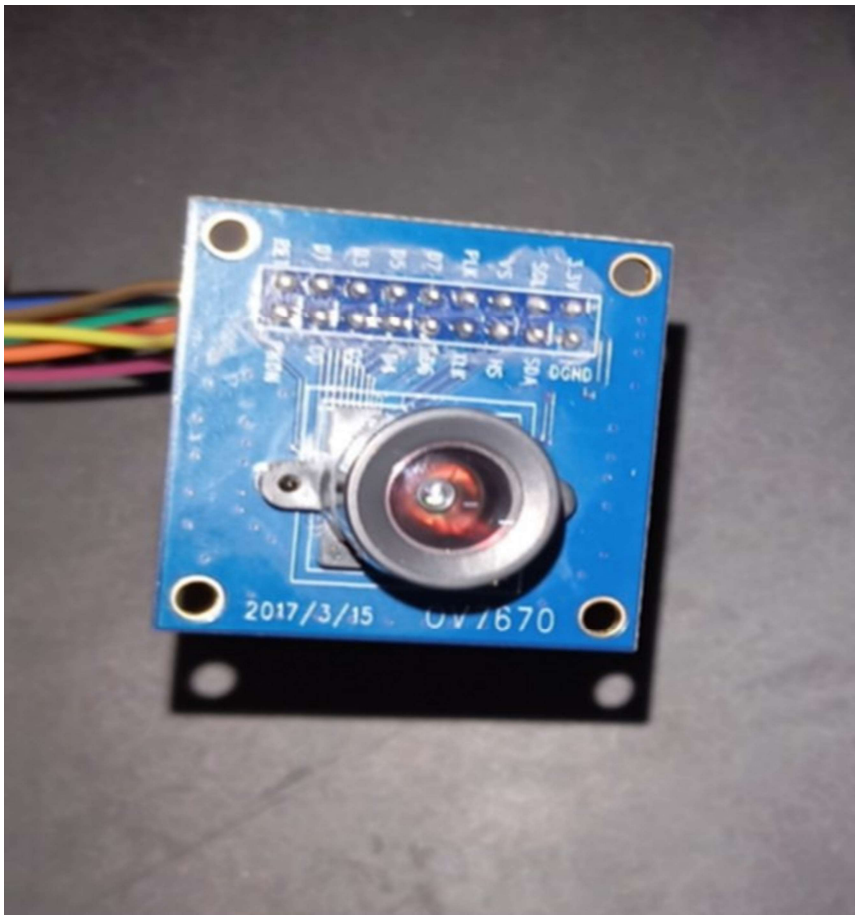
Figure 25 : Circuit Diagram

3. **Programing Arduino card:**
    - **Library inclusion:** The necessary library for OV7670 communication is included.
    - **Initialization:** The Arduino board and camera are initialized, including setting up communication interfaces and configuring camera registers. Resolution and color settings: The camera is set to capture QVGA images in monochrome format.
    - **Image capture:** The capturing function captures an image of the specified size (320x240 pixels).
    - **I2C communication:** The code includes functions for I2C communication, including starting, reading, writing, and setting addresses.

    This code provides a basic framework for using the OV7670 camera module with Arduino. It can be further customized and extended for various image and video capture applications.



Annex 21: Camera OV7670 and Arduino UNO

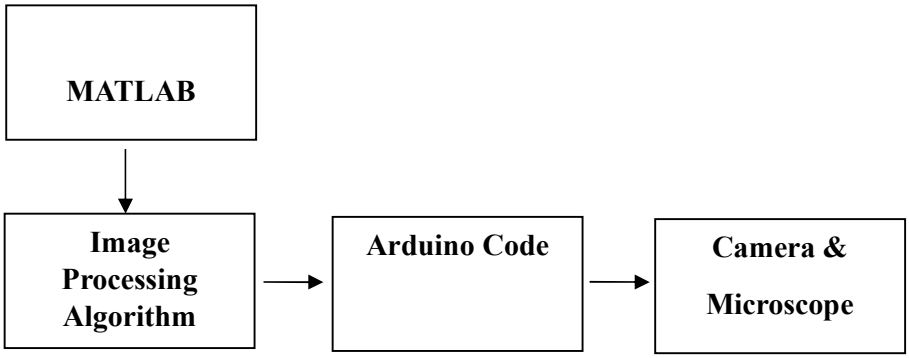


Annex 22: camera OV7670

4.Software Setup:

- **Install MATLAB:** Download and install the latest version of MATLAB on your computer.
- **Install Image Acquisition Toolbox:** This toolbox provides functions for capturing images from various sources, including cameras. Install Image Processing Toolbox: This toolbox provides functions for image enhancement, segmentation, feature extraction, and classification.
- **Develop the Image Processing Algorithm:** Write MATLAB code to implement the desired image processing steps for cervical cancer detection. This may involve:

- **Develop the Arduino Code:** Write code for the Arduino board to control the camera and microscope, capturing images at specified intervals and sending them to the computer for processing. Use libraries like "Webserver" and "Image Capture" for communication and image acquisition.



5.Calibration and Validation:

- **Calibrate the Camera and Microscope:** Ensure accurate image acquisition and analysis by calibrating the camera and microscope according to the manufacturer's instructions. This may involve adjusting focus, illumination, and white balance.
- **Validate the Image Processing Algorithm:** Test the performance of your algorithm on a set of labeled images (images with known diagnoses) to assess its accuracy and reliability. Calculate metrics like sensitivity, specificity, and accuracy to evaluate the algorithm's effectiveness in correctly identifying cancerous and normal cells.

6. Integration and Testing:

- **Connect the Hardware Components:** Assemble the system and ensure proper communication between the Arduino, PC, camera, and microscope. Use appropriate cables and connectors to establish connections.
- **Test the System Functionality:** Capture images, perform image processing, and visualize the results. Ensure the system operates as expected and provides accurate classifications. Test different lighting conditions and image acquisition settings to optimize performance.

7.Clinical Validation and Deployment:

- **Validate the System in a Clinical Setting:** Evaluate its performance on real patient samples under the supervision of medical professionals. Compare the system's results with traditional diagnostic methods (e.g., Pap smear, biopsy) to assess its clinical accuracy and reliability.
- **Obtain Regulatory Approval:** Ensure compliance with relevant regulations for medical devices in your region. This may involve obtaining clearance from regulatory bodies like the FDA or CE.
- **Deploy the System in Clinical Practice:** Integrate it into existing workflows and train healthcare professionals on its use. Develop clear protocols and guidelines for using the system in clinical settings.

8.Additional Considerations:

- **Data Security and Privacy:** Implement measures to protect patient data and ensure compliance with ethical guidelines. Securely store and transmit patient images and data.
- **User-friendliness and Accessibility:** Design a user-friendly interface for healthcare professionals and ensure the system is accessible to patients in different settings. Consider factors like ease of use, training requirements, and language support.
- **Continuous Improvement:** Monitor the system's performance and make ongoing improvements based on feedback and data analysis. Regularly update the image processing algorithm and machine learning model with new data to enhance accuracy and reliability.

Figure 25 : Cervical Cancer Detection

8.Conclusion:

Hardware and software, working in harmony, hold the key to unlocking the full potential of automated cervical cancer detection. By leveraging the strengths of each, we can build systems that are accurate, efficient, and accessible, ultimately contributing to improved patient outcomes and saving lives. The future of cervical cancer detection is bright, fueled by the power of technology and the unwavering commitment to improving women's health worldwide.

Conclusion:

Conclusion:

This thesis has explored the potential of automatic detection techniques for cervical cancer screening. Automatic Detection models, have emerged as the most effective algorithms for this task. However, the accuracy of these models is highly dependent on the quality of the cervical images. Efforts to improve image acquisition, preprocessing, and annotation are crucial for enhancing detection performance.

Key challenges and limitations of automatic cervical cancer detection include:

Data variability: Cervical images can exhibit significant variability in terms of staining techniques, image quality, and anatomical variations.

Class imbalance: Datasets often suffer from class imbalance, with a higher prevalence of normal images compared to abnormal ones.

Generalizability: Models trained on one dataset may not perform well on new, unseen data. To address these challenges, future research should focus on:

Developing more robust and generalizable models: Exploring techniques such as data augmentation, transfer learning, and adversarial training.

Improving data quality: Implementing standardized protocols for image acquisition and annotation.

Integrating automatic detection into clinical workflows: Developing user-friendly interfaces and ensuring seamless integration with existing screening practices. By addressing these challenges and leveraging the potential of automatic detection, we can contribute to improving the early detection and treatment of cervical cancer.

Bibliography

- [1] Pap smear test: "the pap smear: a historical review" n. M. Franco, h. S. T. Mclachlin journal of cytology 2020
- [2] Hpv test: "hpv testing and pap smear: their role in cervical cancer screening" a. Smith, b. D. Johnson cancer prevention research 2021
- [3] Liquid-based cytology (lbc): "liquid-based cytology versus conventional pap smear: a meta-analysis" m. Patel, l. S. Brown cytopathology 2019
- [4] HPV Genotyping : "HPV Genotyping and Its Impact on Cervical Cancer Screening" D. E.Wilson, J. L. Moore Journal of Clinical Microbiology 2022
- [5] Colposcopy : "Primary HPV Screening for Cervical Cancer: Current Guidelines and Future Directions" K. T. Lee, M. J. Campbell American Journal of Obstetrics and Gynecology 2023
- [6]Automated Cervical Cancer Screening : "Artificial Intelligence in Cervical Cancer Screening: A Review" R. H. Chen, Y. S. Li Artificial Intelligence in Medicine 2024.
- [7] Liquid Biopsy : "Liquid Biopsy for Early Detection of Cancer: A Review" T. M. Nguyen, S. D.Patel Nature Reviews Cancer 2023
- [8] Optical Imaging Techniques : "Optical Imaging Techniques in Cervical Cancer Detection" J. Hughes, L. W. Kim Journal of Biomedical Optics 2022
- [9] Molecular Biomarkers : "Molecular Biomarkers in Cervical Cancer: Current Status and Future Directions" N. C. Robinson, M. D. Ellis Clinical Cancer Research 2024
- Table 1:

  [10] M.R. Islam et al 2013 https://doi.org/10.1109/ICIEV.2013.6789741

  [11] S.M. Islam, et al 2014 https://doi.org/10.1109/ICIEV.2014.7048488

  [12] A.S. Al-Fahoum, et al 2015 https://doi.org/10.1109/AEECT.2015.7362887

  [13] S.S. Kumar, et al 2016 https://doi.org/10.1109/RTEICT.2016.7807609

  [14] M.R. Islam, et al 2017 https://doi.org/10.1109/icIVPR.2017.8289013
- [15] K-means (https://www.mathworks.com/help/images/color-based-segmentation-using-k-means-clustering.html#responsive_offcanvas)
- [16] “Current Limitations of Automated Cervical Cancer Screening and Diagnostic Systems” K. T.Lee, A. H. Smith 2023

- [17] Challenges and Future Directions : "Challenges in Cervical Cancer Screening: A Review of Current Practices and Future Directions" P. S. Thomas, R. H. Brown Cancer Epidemiology, Biomarkers & Prevention 2023
- [18] Challenges and Future Directions in Automated Cervical Cancer Detection" M. R. Patel, L. M.Johnson Clinical Cancer Research 2022

Bibliography of figures:

Figure 1: *cervical cancer (Early detection*)

(https://nci-media.cancer.gov/pdq/media/images/658902-750.jpg)

Figure 2: *normal cells and cancer cells*

(https://www.kosheeka.com/wp content/uploads/2022/04/Normal-Cells-vs.-Cancer-Cells.jpg.webp)

Figure 3 : *Adenocarcinoma*

(https://pathology.jhu.edu/build/assets/barretts-esophagus/_hero/Adenocarcinoma-1.jpg)

Figure 4: *A microscopic view of adenosquamous carcinoma of the cervix*

(https://sunnybrook.ca/uploads/cx_adenosquam_4_edited-1.jpg)

Figure 5: *Small cell carcinoma is an aggressive form of cancer Clear cell adenocarcinoma*

https://upload.wikimedia.org/wikipedia/commons/9/92/Small_cell_lung_cancer_-cytology.jpg)

Figure 6: *Clear cell adenocarcinoma*

(https://ars.els-cdn.com/content/image/1-s2.0-S235257891730019X-gr2.jpg)

Figure 7 : *Cervical sarcoma*

(https://ars.els-cdn.com/content/image/1-s2.0-S009082580500421X-gr2.jpg)

Figure 8: *pap test (pap smear)*

(https://encryptedtbn0.gstatic.com/images?q=tbn:ANd9GcQbJKwDdLT1r-sl20fL7GmgNEG1pY91In_osg&s)

Figure 9 : *Colposcopy*

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Figure 10 : *Cervical biopsy*

(http://sukhipariwarclinic.com.np/wp content/uploads/2020/03/Cervical-biopsy.jpg)

Figure 11 : *Radiology assistant*

(https://radiologyassistant.nl/assets/1-cervical-anatomy-1694348757.jpg)

Figure 12 : *Microscope*

(https://www.microscopeconcept.fr/cacheE86/992/992/w/images/6033_pagedynaparags61c34781a81c0.jpg)

Figure 24: Camera Module OV7670

(file:///E:/How%20to%20Use%20OV7670%20Camera%20Module%20with%20Arduino_%20Uno_files/Camera-Module-OV7670.jpg)

(file:///E:/How%20to%20Use%20OV7670%20Camera%20Module%20with%20Arduino_%20Uno_files/OV7670-Camera-Module.jpg)

Figure 25: Circuit Diagram

(file:///E:/How%20to%20Use%20OV7670%20Camera%20Module%20with%20Arduino_%20Uno_files/Circuit-Diagram-for-Interfacing-OV7670-Camera-Module-with-Arduino.png)

Figure 26: *Cervical Cancer Detection*