

Automated & Easy Diagnosis of Cervical Cancer From Onsite Easy Colposcopy Images

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Abstract

Lifestyle and early diagnosis can bring a drastic change in Cervical cancer patient Infections when diagnosed early enough that makes it easy to prevent. By the time symptoms appear, cancer might have manifested itself and begun to spread. Due to poor access to preventive and treatment services, a vast number of unfortunate deaths occur needlessly. Enhancing the prevalent method of treatment and diagnosis, deep learning models have been proved to be more precise and accurate than mere Visual Inspection by specialists. AI-assisted colposcopy reduces time and effort it takes for a gynecologist to gain an expertise and thus spares more time to improve other skills, training and activities. Here, we use Supervised(unsupervised) algorithms in order to classify the colposcopy images. To attain our target, we collect a large number of image datasets requested to ABC hospital and are categorized by our system to different stages of cancer, results of which can be further analyzed by specialists to imply appropriate clinical procedures of cure. The successful deployment promotes low-cost mobile technology to facilitate millions of women across the country who earlier had limited access to life-saving cancer tests. As the morbidity and mortality rates of cervix cancer are pretty high, early detection and treatment of the abnormal tissues or pre-cancerous cells is the ultimate solution to it. This study is useful to diagnose an early metamorphosis of cancerous cells more accurately and hence helps to drop down the death rate even in any low-middle resources areas of the country.

Keywords: Cervical Cancer, Deep learning, Colposcopy, Pap smear and HPV

Introduction

Cervical cancer stands the second most common cancer amongst the women worldwide. World Health Organization (2010) ranked Cervical Cancer as the 1st most common gynecologic malignancies among women age 15 to 44 years of age in Nepal (Pandey & Karmacharya, 2017). Cervical cancer is the first cancer recognized by the WHO to be 100% attributable to an infection. Although it is said you beat cancer by your lifestyle but the survival rate varies between cancer types, ranging from 98% for testicular cancer to just 1% for pancreatic cancer (*Cervical Cancer - Statistics*, n.d.). Of the major strategies to beat the high rate of cancer, one of them is to screen 70% of women of age between 35 and 45 years and 90% of women managed appropriately by 2030. (Xue et al., 2020) The crude incidence rate of cervical cancer in Nepal is 24.2 per 100,000 women per year (Gyawali et al., 2015). on one of the experiments conducted, According to the HP Information Centre Nepal, 2,942 new cases are diagnosed every year out of which 1,928 women die. (Mulmi et al., 2019) Therefore, It is an urgent health issue for us as 83 percent of all new cases of cervical cancer and 85% percent of global deaths occur annually in low and middle income countries (LMICs). (*Cervical Cancer Screening And Prevention Project In Nepal — Karuna Foundation Nepal*, n.d.)

“An ounce of cancer prevention is worth a ton of cancer cure.” Robert A. Wascher

The introduction of pap test has reduced the instances of cervical cancer to a greater extent in high resource settings but it has a high false negative result. So as to increase the conformity of the screening, HPV test

has been implied. HPV testing has greater sensitivity than pap smear test but there's a slight chance of false diagnosis since not every HPV develop into cancerous stage. Both pap smear and HPV testing rely upon the invasive mechanism of sample collection and are exported to laboratory for observation. Depending upon the availability of resources and experts, the test report can take several days or sometimes even weeks to arrive accounting for the high rate of drop outs on flow up. People fail to catch up the schedule for further treatment. Providing an immediate result at the site of sample can play a vital role in descending rate in follow up loss curve to bottom line as secondary advises can be offered with no loss in time. Our algorithm can be promising in accuracy in comparison to pap smear test as it searches for cancerous lesions(CIN2+) and then gets away from over diagnosis that occurs with HPV testing. Patients would benefit from immediate results at the point of care without having to wait weeks merely for test results which is common for Pap tests. The spontaneous results provided by AI automated system could assist in rapid risk-stratification and then patients can be immediately referred to secondary screening, to treatment or to routine screening.

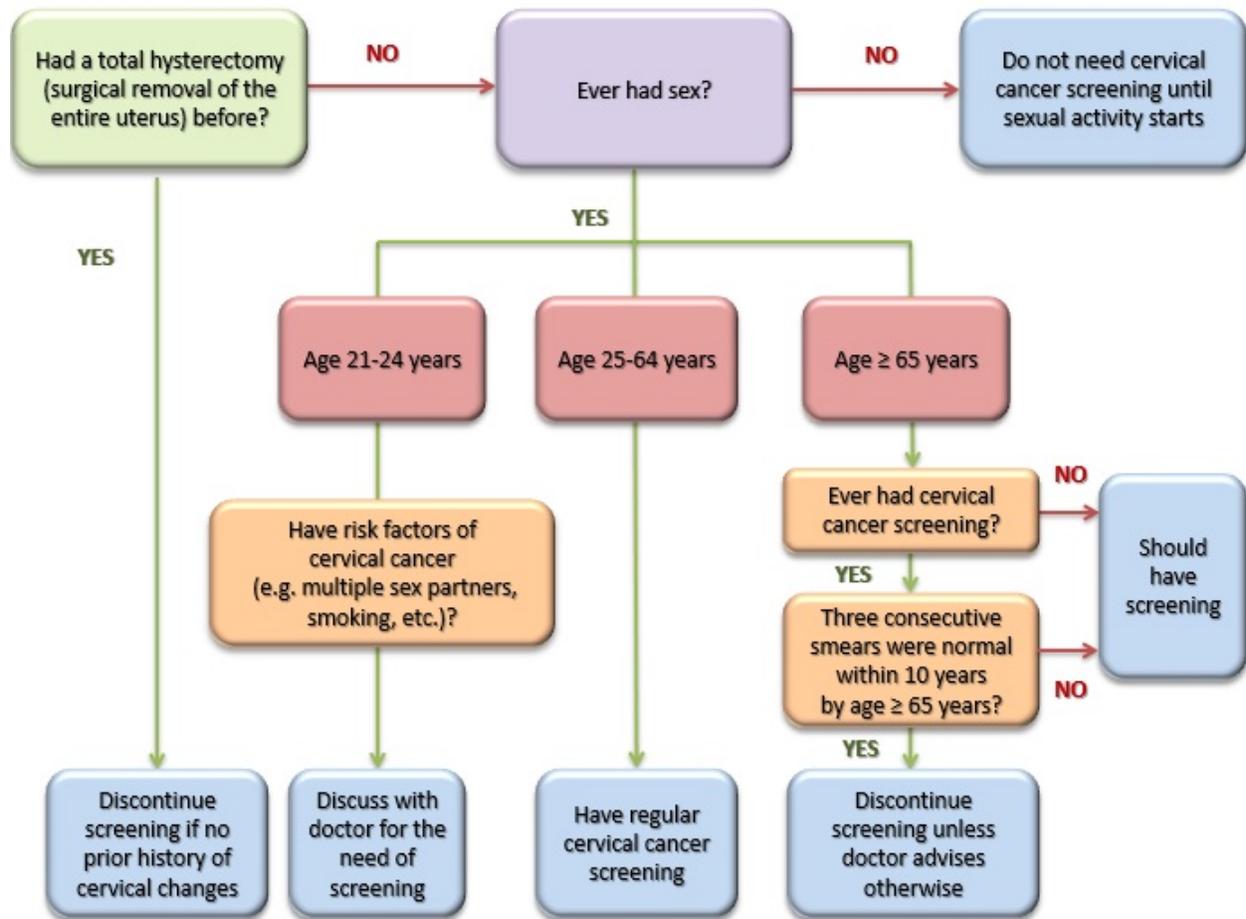


Figure 1: Decision flowchart for cervical cancer screening: *(Cervical Screening Programme - Cervical Smear, 2012)*

The development of cervical cancer is a very slow process. It starts with a precancerous condition called dysplasia and can be detected by pap smear test. Most of the cervical cancers are caused by Human Papilloma Virus (HPV) which could be both Oncogenic & Non-oncogenic in nature. When diagnosed early, the 5-year

survival rate for women with invasive cervical cancer is 92%. (*Cervical Cancer - Statistics, n.d.*) It is one of the easiest cancers to prevent, with regular screening tests and follow-up.

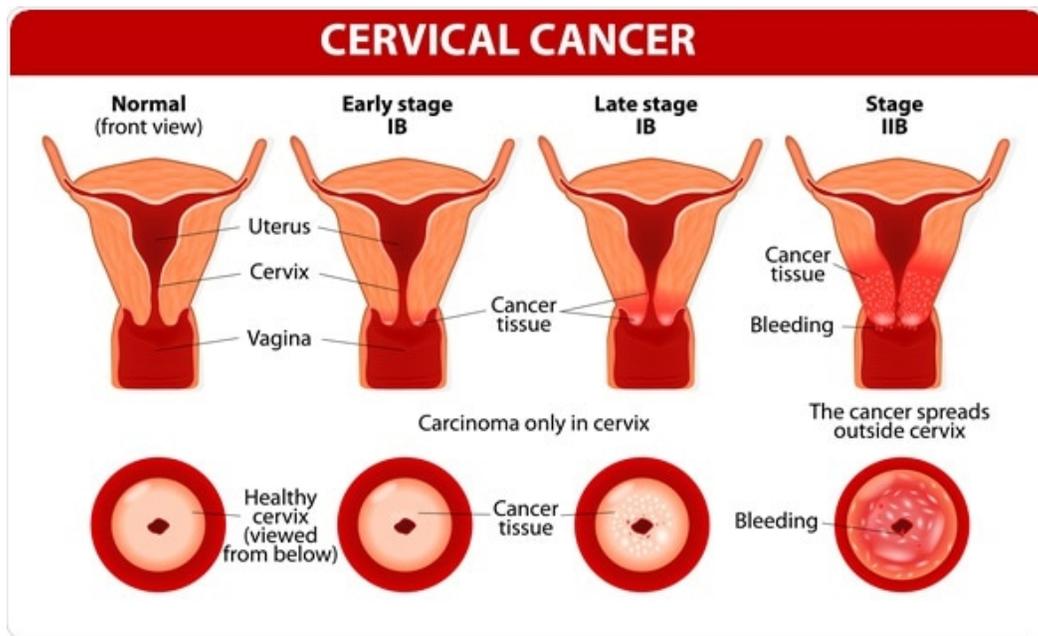


Figure 2: (*HPV and Cervical Cancer, n.d.*)

It has a long precancerous phase of around 10 years before it develops into an invasive cancer. Therefore, being aware of any sign and symptoms of cervical cancer can also help avoid delays in diagnosis. Colposcopy is widely used for screening cervical cancer which is an easily preventable disease if diagnosed early enough. (*Cervical cancer - Treatment, n.d.*) Prevalence of cervical cancer is high among Nepali women and a large majority of women in rural areas do not have easy access to experts who can diagnose the cancer using cervical images from colposcopy or even from images taken from mobile phones. In this work, we propose automated deep learning based methods for early and easy diagnosis of cancerous tissues in colposcopy or mobile phone images so that it greatly improves the chances of successful treatment of pre-cancers and cancers.

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“Cancer affects all of us, whether you’re a daughter, mother, sister, friend, coworker, doctor, or patient.” – Jennifer Aniston

Because of the inappropriate routine screening (uneasy access to service, expensive diagnosis, fear of being wrongly diagnosed, fear of being accused of STDs, Shyness to visit male gynecologists, etc) women from

the remote communities seek for service only after they have developed unavoidable symptoms often bearing the advanced stage cancer for long. By the time symptoms appear, cancer may have manifested itself and begun to spread. Due to poor access to preventive screening and treatment services, a vast number of cervical cancer deaths occur unnecessarily. A study revealed that the urban population in Nepal, with its high literacy rate and access to treatment, benefits more from screening programs (coverage 4.7%) than the rural population of Nepal (coverage 2%). (Gyawali et al., 2015). Routinely functional equipments, lack of qualified colposcopists, and socioeconomic conditions contribute in declining screening numbers. In a research, Out of 1033 participants 628 (61%) never had Pap tests and 405 (39%) had at least one Pap test during their life time (Sherpa et al., 2015). The coverage rate for cervical cancer screening services is (2.4%) in Nepal (Gyawali et al., 2015). Similarly, Routine screening programme has reduced its mortality by more than 70% in developed countries (Sherpa et al., 2015).

When there are no bounding constraint of finance and resources, screening of cervical cancer begins with the Pap smear to test HPV leading to colposcopy guided biopsy and respective treatment as per the reports obtained. . In Colposcopy, the low quality microscope is used to observe the highlighted cell changes after reacting with the acetic acid or lugol's solution.(Asiedu et al., 2019) dSmooth and pink tissues indicate a normal cervix. With acetic acid, the cancerous cells turn whitish while normal remains pink while with lugol's solution, the probable cancerous cells turn yellowish while normal cells become darker. This contrast helps to find the borderline between suspicious cells and normal cells.

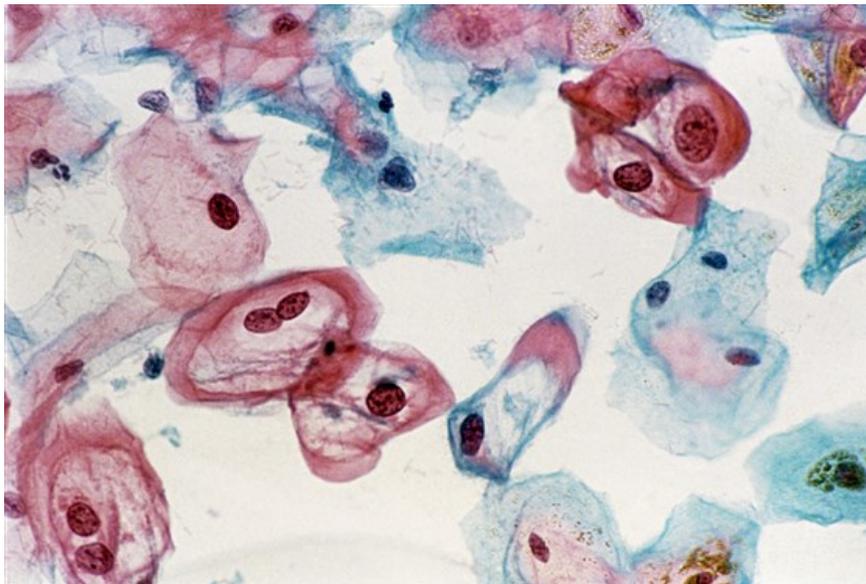
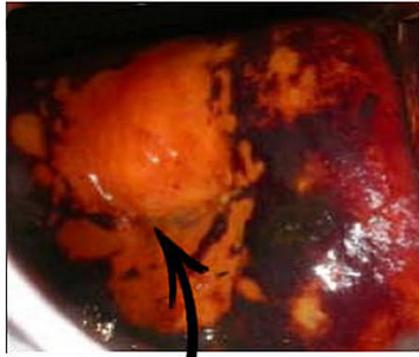


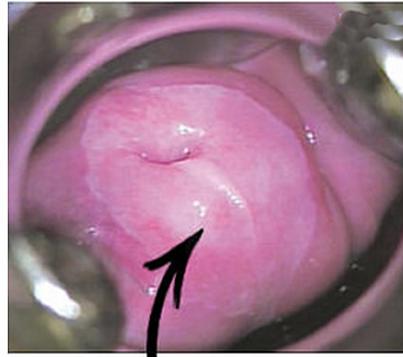
Figure 3: HPV cervical infection. Light micrograph of a cervical smear revealing epithelial cells infected with the human papilloma virus (HPV).Science Photo Library / Getty Images

Lugol



Yellowish area

Acetic acid



Whitish area

Figure 4: Lugol Test vs Acetic Acid Test in Visual Inspection (*Lugol Vs Acetic Acid, n.d.*)

Suspicious cells are extracted for further pathological confirmations. Pre-Cancer females are cured by excision of the damaged/suspicious parts whereas ones with cancer are recommended to a local or systematic therapy basing upon the stage of invasive disease they're in. In settings restricted with financial resources, HPV testing is the best suited alternative to pap smear. Also, unnecessary referral of women to confirmations make it less expandable. Particularly speaking, due to the poor resolutions image being captured, VIA is not yet flourishing.

Our traditional system of diagnosis rely mainly on the shape, color, and/or texture features of the suspicious cells as well as their combinations. Cytology of suspicious cells are problem-specific and have shown to be contrasting in different medical images and that leads to mould a system that lacks the ability to represent high-level problem domain concepts with poor model generalization ability. The inconvenience of carrying heavy equipments to the site for community checkup has limited the wide use of colposcopy as of yet.

Various researches have been conducted regarding the feasibility and efficiency of the automated diagnosis of cervical cancer by deep learning algorithms and they show that it positively aids in tuning the diagnostic performance eventually aiding to eliminate the cancer globally. (Xue et al., 2020) . The accuracy of automated Visual evaluation was found to be 90% which is significantly higher than pap smear test(71%) in current system and even outperformed the inference from specialists for the same images. (*Automated Visual Evaluation (AVE) explained: Everything you need to know about the new AI for cervical cancer screening — MobileODT, n.d.*) The advanced technologies build cutting-edge tools for healthcare providers, extending the capabilities of the AI System to help them save more lives. Artificial Intelligence (AI)automated Diagnosis system has tremendous promise to support healthcare providers better care for their patients. It can facilitate patients for the best possible diagnosis at the right time, enable the medical system to determine the best next steps for that patient, and guide patients to find the resources to address the disease. In deep learning based automated classification, the major task includes feature abstraction and combination of those features/diagnosis of contrasts in cervigrams to gain highly accurate results in less time. Coding Network with Multilayer Perceptron (CNMP) combines high-level features that are extracted from a deep convolutional neural network and some selected traditional features.z Firstly, a deep convolutional neural network is trained as a coding network in a supervised manner. Then, it enables us to code the raw pixels of medical images into feature vectors which represent high-level concepts for classification. Secondly, a set of selected traditional features is extracted based on prior knowledge of clinical images. Finally, an efficient model is designed based on neural networks to fuse various feature groups obtained from the first

and second steps. In a research conducted, the proposed approach is evaluated on two benchmark medical image datasets: : HIS2828 and ISIC2017. An overall classification accuracy of was found to be 90.1 and 90.2, respectively, which are higher than the current successful methods.(Lai & Deng, 2018)

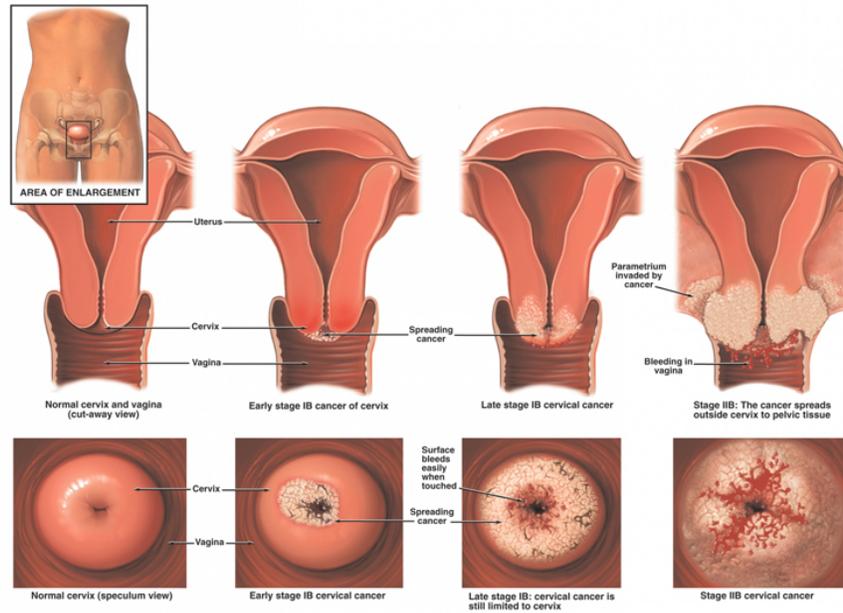


Figure 5: Stages of Cancer and tissues (*Cervical Cancer*, n.d.)

SVM (Support Vector Machine), KNN (K-Nearest Neighbor), K-SVM (Kernel Support Vector Machine), Random Forest Tree, Decision Tree works with an accuracy of 97.20%, 95.10%, 96.50%, 98.60%, 95.80% respectively in an algorithm used for the breast cancer detection.(Awatramani & Hasteer, 2019) It directly trained the deep convolutional neural network called the coding network to extract high-level features rather than using domain-transferred convolutional neural networks such as domain-transferred convolutional neural networks (DT-CNNs). In another research, AI classifier with a convolutional neural network catenating with an HPV tensor was developed and trained. The accuracy of the AI classifier and gynecological oncologists was found to be 0.941 and 0.843, respectively. (Miyagi et al., 2019). Using multimodal convolutional Network having inputs (i) Experts interpretation of 10k images and (ii) patient clinical history (age, pH value, pap smear, HPV reports) to feed the classification model yielded 88.91% accuracy, 87.83% sensitivity and 90% specificity.(Asiedu et al., 2019) An algorithm that pre-processes images to reduce specular reflection, automatically segments a region of interest from cervix for analysis, extracts colour and texture based features and utilizes a support vector machine for binary classification of VI and VILI images ROC curves generated from classifier determine area under curve that indicates how well a model predicts classes which achieves a sensitivity(81.3%), specificity(78.6%) and physicians for same data was sensitivity(77%), specificity(51%). The image region was segmented by using Gabor's filter.(Asiedu et al., 2019)

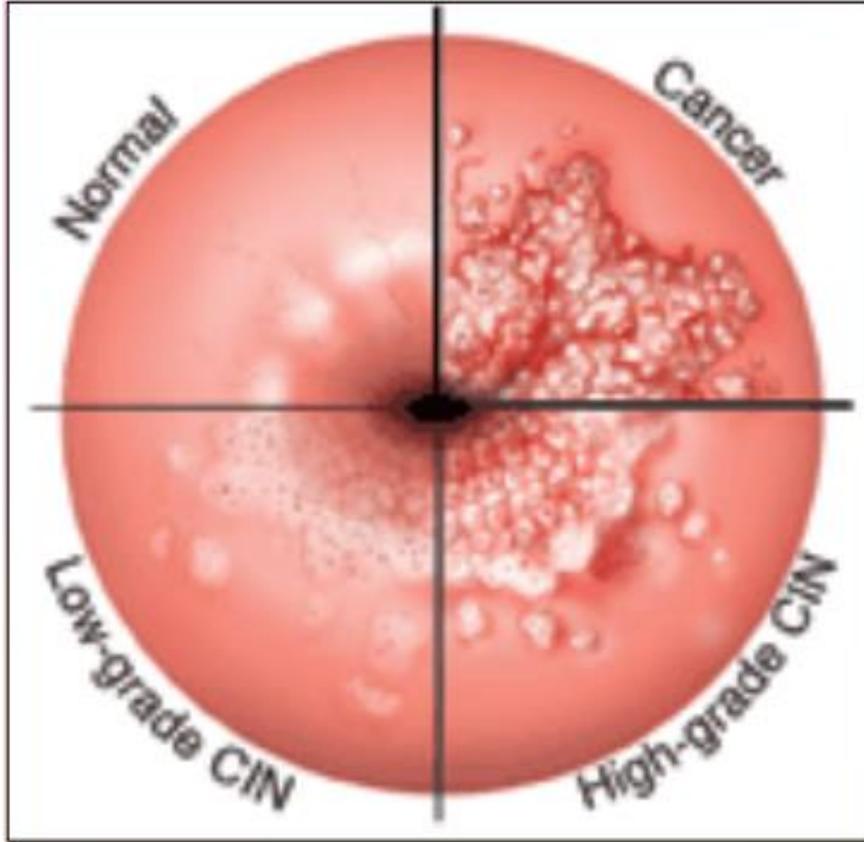


Figure 6: Differences of cells(Aina et al., 2019)

HPV types and colposcopy were associated with pathological results, but not with each other. the association among the pathological results, colposcopy diagnosis and HPV type may be a reason for high accuracyThe highest accuracy for HSIL of the best AI classifier combined with HPV types for a test dataset was 0.941 (48/51) when the number of the augmented training dataset was 1,212, the value of L2 regularization was 0.02, and the image size was 50×50 pixels. (Miyagi et al., 2019) When the performance of the AI classifier is further improved in accuracy, sensitivity and specificity for classifying SILs, gynecologists may be able to obtain more precise classification without requiring a colposcopy specialist. The major hurdle for deep learning based system is the effective extraction of features from a small medical image dataset & quick and efficient fuse of different types of features from different models. Problems arise due to the high resolution of the medical images and the small dataset size and the system of deep learning models suffer from high computational costs along with limitations in the model layers and channels.

The challenges though can be effectively tuned to gain efficient results. We have faith in AI as it has exceeded human experts in the field of games with perfect results and also human experts in the field of games with perfect results. AI-assisted colposcopy may reduce the time and effort it takes for a gynecologist to become a colposcopy expert resulting in more time to improve other skills, training and activities. The the use of AI for predicting live births from blastocysts, to a level similar to that of specialists, may result in time saved for embryologists, reducing the financial costs of training(Miyagi et al., 2019) Researchers claim that AI becomes able to recognize certain information that conventional procedures cannot, it may also provide more precise diagnosis in practical medicine.(Miyagi et al., 2019)AI classifier may also recognize features that colposcopists do not, such as relative or absolute brightness of acetowhite, complexity of the shape of the lesion, quantitative marginal evaluation of borders and distribution of punctuation density. AI, including

deep learning, can acquire numerical data to indicate the features of an image and use the numerical data indicating the features of colposcopy images and the numeric tensor data of HPV types. This is an important feature of AI, which may be the second reason for high accuracy in this study from the perspective of computer science. Batch normalization allows the use of high learning rates. This architecture may be the third reason for high accuracy in the present study.



Figure 7: <https://www.opthalmologytimes.com/view/artificial-intelligence-medicine-good-bad-and-scary>

AI is not meant to replace clinical manpowers instead, it is primarily focused on boosting the diagnostic potential of laboratory tests. As of yet, experts are trained to recognize certain patterns of microscopic or colposcopic suspicious cells and infer accordingly. Today, we march towards training neural networks to take the job in recognizing the patterns using thousands images and their ground truth outcomes. This will allow reliable test methods to reach every humans on earth who has normal cell phones and internet connection. The use of AI automated colposcopy is helpful for experts and non-experts both. For experts, the system provides a second opinion and for non-experts, the system provides an immediate examination for low resources settings and makes on site screening possible which had previously been limited by lack of required resources.

Existing Competition:

[MobileODT](#) has developed and sells the Enhanced Visual Assessment (EVA) System, a digital toolkit for health care workers of every level to provide expert services to patients, anchored at the point-of-care by an FDA-approved, intelligent, mobile-phone based medical device. Combining the algorithmic power of biomedical optics with the computational capabilities and connectivity of mobile phones, MobileODT's connected, intelligent medical systems can be used everywhere, under nearly any conditions. MobileODT's first product, the FDA approved EVA System for colposcopy, is in use by health providers in 31 hospital systems across the US, and in 22 countries, to better screen and treat women for cervical cancer and to conduct forensic colposcopy. ([Intel & MobileODT Cervical Cancer Screening](#) — Kaggle, n.d.)

About the Colposcopic Images:

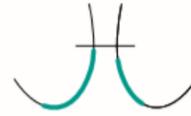
Different transformation zone locations = Different Cervix type

Source: The Cervix, Singer et al, 2006

- Type 1
- Completely ectocervical
 - Fully visible
 - Small or large



- Type 2
- Has endocervical component
 - Fully visible
 - May have ectocervical component which may be small or large



- Type 3
- Has endocervical component
 - Is not fully visible
 - May have ectocervical component which may be small or large



Figure 8: Cervix Type by Transformation Zone

Most of the cervical Cancers begin in the cells in Transformation Zone(TZ). Squamo-Columnar Junction(SCJ) is where two different types of epithelial cells meet and TZ is the area between the original SCJ and new SCJ. Cervix types and might include hidden lesions and need different approach of treatment.

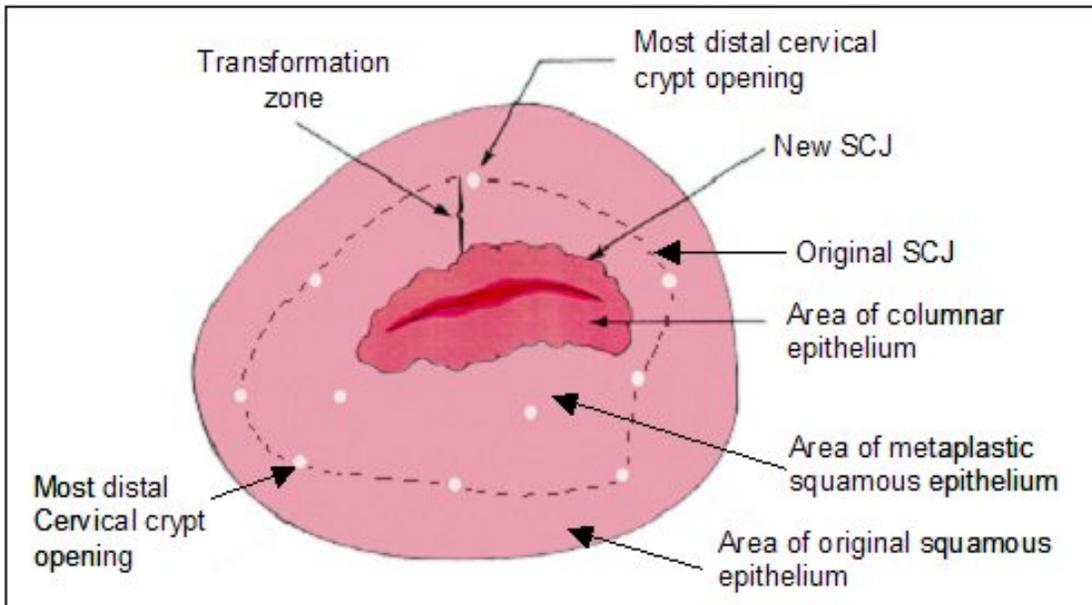


FIGURE 5.1: A method of identifying outer and inner borders of the transformation zone (SCJ: Squamocolumnar junction)

Figure 9: This is a caption

The image dataset we will be using is extracted from the dataset provided by kaggle in the competition where Intel partnered MobileODT in 2017 to challenge kagglers develop an algorithm to accurately identify a women’s cervix type based on images. The major motivation behind this was that it will prevent ineffectual treatments and gives access to healthworkers provide proper referral for the cases that require further serious treatment.

The different types of cervix in given data set are all considered to be normal(non-cancerous) but since the Transformation Zones are not always detectable visually, some of the patients might require further testing while some might not. This point of care decision is vital for the patient. On the other hand, identifying the Transformation Zones(TZ) is not a easy job for health workers, therefore AI-based automated system will significantly enhance the Quality and Efficiency of cervical cancer screening for these patients.

Properties of our Dataset:

The chart below shows the folder structure of our image dataset.

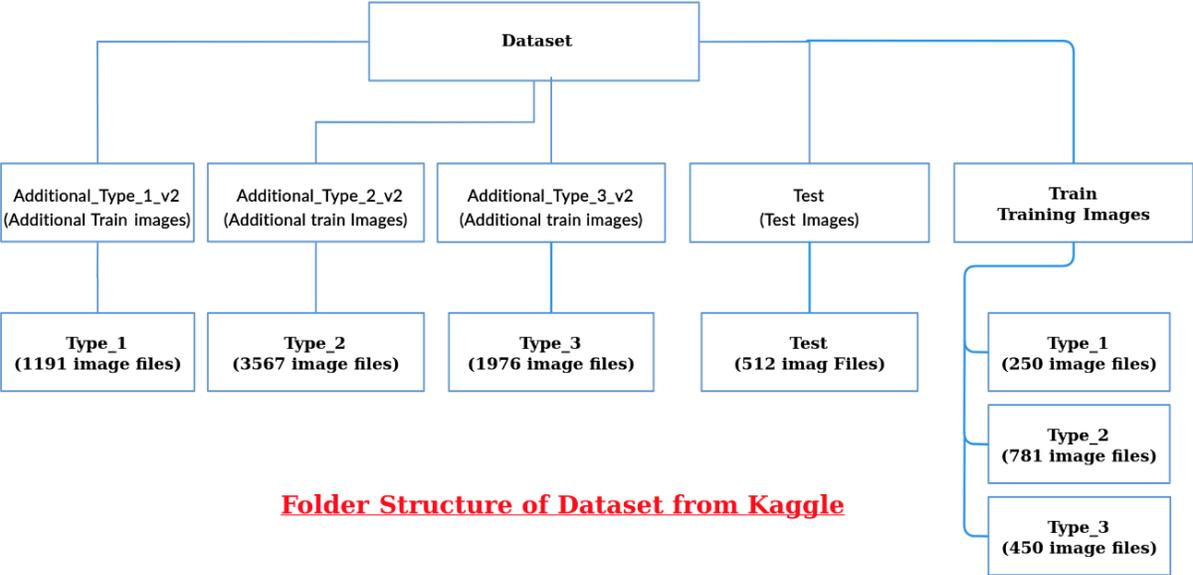


Figure 10: Organization of Image datasets into Train and test folders

File Descriptions:

- 1) **Additional_Type{x}_v2:** These images help us train our models. Some of these images come from duplicated patients, therefore images might look alike as they are taken in the same session; while some cases are not included because of the image quality. All the images all labeled and are organized in respective categories as: Type_1, Type_2, Type_3
- 2) **Test:** These images are all in same folder and as per the competition, these are the first stage test images.
- 3) **Train:** This is a training set image organized into three distinct folders under the labelled categories as: Type_1, Type_2, Type_3

PS: solution_stg1_release.csv contains the solution of stage 1 test data label images. test_stg2.7z is the 2nd stage test set whose password is “byecervicalcancer”.

Issues with Images provided:

There are several issues with the image dataset provided. The bad images differed to one another by various factors mentioned below and those could still be used or some might have to be discarded. Applying various cautions during the procedure can lead to a good inference at the point of care.

a) Vaginal walls obstruct the view of cervix:

Especially in cases where the patient is overweight or experiencing vaginal atrophy, lax vaginal walls can obstruct the clinician’s ability to view the entire cervix.



Figure 11: This is a caption

solution: use a vaginal retractor to hold them in place or use tip cut condom over the speculum before insertion

b) Shadowing in the Image:

A dark shadow at the bottom of this image preventing full visualization of the cervix. This is caused by incorrect positioning of the light source, or incorrect angle of the colposcope.



Figure 12: This is a caption

solution: Reposition light source to be higher in relation to vaginal canal.

c) Mucus, blood or other substances on the cervix:

A number of substances might accumulate on the cervix, impeding clear visualization.



Figure 13: This is a caption

solution: Extra mucus can be removed with a cotton swab or surgical tongs

d) Speculum Obstruction:

At times the speculum can prevent a clear view of the cervix. This could occur from a misplaced speculum, in which case repositioning the speculum will allow for full visualization of the cervix.



Figure 14: This is a caption

solution: Sometimes, a small adjustment in angle of speculum is enough. try adjusting the position of colposcope to make sure cervix is in the centre of the image and then zoom further.

e) Blurry Images:

Sometimes images that are captured with a digital colposcope can appear blurry. This is when the entire image appears ‘fuzzy’ and/or the image looks like it has been ‘pulled’ in one particular direction.



Figure 15: This is a caption

solution: Try to keep the colposcopic device still and balanced until focus

f) Image is out of focus:

Images have only part of the image out of focus or all the image looks pixelated but there isn't a warping of the image.



Figure 16: This is a caption

solution: On positioned balanced, focus can be adjusted to achieve a sharp image.

g) Only part of the cervix is in view:

Somwtimes we find that the image only shows part of the cervix but we need to see more in order to make an accurate diagnosis.



Figure 17: This is a caption

solution: try adjusting focus around the portion to be captured

h) Acetic Acid issues:

The timing of acetic acid application and the appropriate amount of time given for all lesions to present themselves is crucial to making an accurate diagnosis.

solution: Use timer to note the scenerio

Image Pre-Processing

For the processing of raw image datasets the following steps are to be conducted:

- Resize all images to same size (32 * 32* 3)
- Normalize pixel values
- Apply image deformations(random scaling+ rotations) for regularization
- Store data in a loadable numpy format

For preparing model, using CNN is a tedious choice as we have to build an image classifier. "We shall be using:

- Two 2D-Convolutional Layers followed by Max Pooling Layers
- ReLU activations
- Dropout between output of second convolutional block and input of fully connected layer
- Two fully connected layers for classification with dropout
- Hyperbolic Tan activation for FC-1 layer
- Softmax activation for FC-2 layer (Obvious choice, given a multiclass classification problem)
- Adamax optimizer - a variant of Adam based on the infinity norm (*darshanbagul/CervicalCancerKaggle, n.d.*)

Future considerations:

- It is believed a higher score can be achieved by Transfer Learning. Fine tuning a pretrained model such as Inception-V3, VGG19, ResNet-50 can definitely boost the model accuracy.
- It was reported improved results by using R-CNN like approach i.e generating bounding boxes around regions of interest and generating probability predictions."

With the advent of AI capabilities, remote collaboration, and improved workflow via the mobile EVA System, more women in India will have access to cervical cancer screening through non-expert analysis at the point of care. The EVA System is currently in use in 29 countries and over 50 US health systems. The clinical study to be conducted at Apollo Hospital Centres throughout India will improve the AI algorithm used in cervical cancer detection by comparing cytologic cotesting to the algorithm performance, using biopsy as ground truth. The capabilities of using the EVA System along with the algorithm will greatly improve the lives of women across India by providing on the spot diagnosis and improved patient tracking through the secure digital platform. A previous pilot conducted in six Apollo Hospital Centers to assess the value of the EVA System on improving patient and provider experience found that [the EVA System helped early detection of cervical cancer for almost three times as many women compared to those who were identified positive with Pap smear](#). The study was coordinated by Apollo Research and Innovations (ARI), the research division of Apollo Hospitals Group." (*MobileODT and partners to launch first wide-scale deployment of AI screening for Cervical Cancer — MobileODT, n.d.*)

b) Objectives:

In order to avoid the invasive cancer diagnosis system, and enhance the easy diagnosis, we have thought of diagnosis/detection of Cervical cancer by Transformation zones. AI-assisted system classifies the type of cervix easily so that it helps health workers to make a quick on site diagnosis. The major features are:

1. **Capture:** Achieve high-quality images and video (future work when mobile app is developed, we focus on the Web app for now, therefore the image dataset are captured from other devices)
2. **Document:** Mark biopsy locations highlight, and add relevant notes for documentation, referral or case-sharing.
3. **Collaborate:** Securely share patient cases with colleagues or relevant organizations for assesment.
4. **Educate:** Empower patients, trainees and peers with collaborative image review and remote training.
5. **Analyze:** System administrators can track patient cases and user activities, ensuring clear follow-ups and re-training pathways.
6. **Whole Nepal Analysis:** The outcomes can be visualized in term of age, type of cervix and cancer incidence which can be utilized in developmental decision making process.

c) Scope of the project

-For Patients: It brings expert care to patients doorsteps. Reducing the Hidden burden of healthcare(travel time, time off work, childcare needs, etc.) and makes it easier for petients to enjoy the care they need and reduce loss to follow up.

- Less travel time to appointments
- Immediate advanced care
- Reduced loss to follow up

-For clinicians: It allows primary health care and other advanced care without having to hustle between hospitals. Clinicians can easily get a backup opinion from the remote mentorship and therefore widens the services offered.

- Offer advanced care in own practice
- Remote mentorship
- Immediate second opinion

-For health care networks: It allows healthcare networks to make maximum use of the available human resources. Extending experts to every locality is expensive therefore in multiple locations, healcare workers can still conduct the on site diagnosis by remote specialists consulting via our system. It also improves the patient service satisfaction by reducing the travel time to enhanced care appointments. It can also be expanded to provide remote mentorship.

- Maximize resources
- Extend training programs
- Increased patient satisfaction

Work on Image DATASETS:

A) Check Data

1)check the dataset's image shape, and jpeg file's error or warning

2)check all dataset (stage 1, train, test, additional)

Shape includes size (height, width) and number of color channel (RGB = 3)

shape_1 = height, shape_2 = width, shape_3 = 3

error = blank 0 byte file

warning = Premature end of JPEG file

about 55% data of the image size, This file can't be used.

about 78% data of the image size, this file can be used.

about 75% data of the image size. This file maybe be used.

-Label Box

Label-img python application

-Explain Visual properties of the dataset provided

- Age in years
- Number of sexual partners
- First sexual intercourse (age in years)
- Number of pregnancies
- Smoking yes or no
- Smoking (in years)
- Hormonal contraceptives yes or no
- Hormonal contraceptives (in years)
- Intrauterine device yes or no (IUD)
- Number of years with an intrauterine device (IUD)
- Has patient ever had a sexually transmitted disease (STD) yes or no
- Number of STD diagnoses
- Time since first STD diagnosis
- Time since last STD diagnosis
- The biopsy results “Healthy” or “Cancer”. Target outcome.

(<https://christophm.github.io/interpretable-ml-book/cervical.html>)

(Canfell et al., 2020)

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