PapSmear Image Recording System for Artificial Intelligence Data Collection

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\textbf{Abstract.} Cervical cancer is one of the most leading causes of death for women worldwide. To reduce the mortality caused by cervical cancer, early screening techniques such as pap smear need to be carried out more extensively. For that, the availability of an automatic screening system is essential. In this paper, we proposed a system that can collect the dataset needed to train an Artificial Intelligence (AI) system for the automatic pap smear screening system. The proposed system can be integrated seamlessly to the current pap smear result recording procedure; hence avoiding any possible complication.

\textbf{Keywords:} Pap Smear, Image, Screening, Data Collection, Artificial Intelligence

1. Introduction

Cervical cancer is currently ranked as the second most common cancer-related cause of death for women in the age range 20-39\cite{1}. While this might seem critical, the solution to the problem might already be in our hands. History showed that the use of pap smear for early screening has reduced cervical cancer mortality in the United States significantly\cite{2,3}. Therefore, more intensive use of pap smear outside the United States is potential to reduce the current cervical cancer global mortality rate further. Unfortunately, cervical cancer screening services are scarce outside the developed countries\cite{4}, due to the insufficient number of capable health workers to operate the service\cite{5}.

To answer this challenge, an automatic screening system can be deployed to fill the gap caused by the scarcity of health workers. In the case of papsmear, one of the promising approaches to develop the system is by using Artificial Intelligence (AI) models to screen the pap smear images. Recent studies showed the promise of this approach by demonstrating a drastic performance upgrade of AI for medical images\cite{6–9}. The type of AI used falls in the category named deep learning, which can automatically discover useful features from images\cite{10,11}, unlike the classical image processing system\cite{12}. In biology domain, deep learning can even be used to model more complex data such as protein sequence\cite{13}. The only limitation of deep learning is its requirement for a massive amount of data for optimal performance\cite{14–19}. This limitation can be overcome by developing an effective data collection strategy such as developing an annotation system. However, we noticed that there is no such strategy for the pap smear case. Therefore, we developed a system that can seamlessly be integrated into a pap smear procedure while at the same time can be utilized to store a massive number
of pap smear images for the purpose of AI development. The proposed system replaces the manual process of recording the pap smear result, hence it even helps the health workers to manage the pap smear results while stores the images for future AI development at the same time.

2. Literature Review
The effort of building an annotation system is prevalent in many domain applications. In most studies, the annotation systems were built with the help of Amazon Mechanical Turk (AMT) which details were not published. For example, the ImageNet [20,21] and Ms. COCO dataset [22], the most popular image datasets, were collected with the help of AMT. Only the study by Vondrick et al. [23] that detailed their system that was deployed in AMT. An advanced version of the annotation system, which is integrated with the machine learning training workflow, is also detailed in a publication by Quinn et al. [24]. Other studies also detailed their annotation system that was not deployed using AMT [14,15,25].

In particular for medical image analysis, a commercial annotation tool called NVIDIA AI-Assisted Annotation has been released to assist radiologists at providing annotation for medical image segmentation. The algorithm behind the tool is based on the Deep Extreme Cut algorithm developed by Maninis et al. [26]. Specifically, for pap smear images, we found no study that developed a system to accelerate the annotation process of the images.

3. System Design
To design the pap smear image recording system, we used the class, use case, and activity diagram from the Unified Modeling Language diagram family, as well as the entity relationship diagram to design the database. The use case, class, activity diagram, and entity relationship diagram of the system are elaborated in the sub-section 3.1, 3.2, 3.3, and 3.4 respectively.

3.1. Use Case Diagram
As depicted in Figure 1, the developed system comprises three different use cases: Login, Upload Patient Data, and Edit Patient Data. The system was developed as a web application, in which each use case represents a separate web page of the system. The sole actor in the system, namely the Uploaders, can access these three use cases to help them in providing the annotation of the pap smear images.

![Use Case Diagram](image.png)

Figure 1. Use Case Diagram.
3.2. Class Diagram

The class diagram of the system design is depicted in Figure 2. Because the system was developed using the Model-View-Controller design pattern, the classes in the system acted as either a controller or a model. The controller and the model classes are derived respectively from the CI_Controller and CI_Model class, which is provided in the Codeigniter framework we used to develop the system. Three controllers and three models are employed in the system, which respectively designed to control and provide data for Login, Upload Patient Data, and Edit Patient Data use case.

![Class Diagram](image)

**Figure 2.** Class Diagram.

3.3. Activity Diagram

For a concise elaboration, we split the activity diagram into three diagrams. Each diagram explains the logical flow of the Login, Upload Patient Data, and Edit Patient Data use case. These diagrams are depicted in Figures 3a, 3b, and 3c. As elaborated in Figure 3a, the flow of the Login phase is started from inputting the username and password, which are validated by the system. If the credential is correct, the system will display the main page. If the credential is incorrect, the uploader needs to re-enter his/her username and password. Afterward, the uploader can choose to open the upload or edit page. In the upload page, the uploader is asked to upload pap smear images and provide the patient data whose sample is captured as the uploaded images. After the images have been uploaded and the data has been entered, the data is saved to the database and the system is redirected to the main page. If the uploader chooses to open the edit page, a page listing all recorded patients will be displayed by the system. By choosing one of the patients, the uploader can upload new images, delete the previously provided images, and edit the chosen patient data. If there is any update to the images or patient data, the update will be saved to the database before the system redirects the user to the main page.
3.4. Entity Relationship Diagram

The developed system utilizes two tables: patients and images. The patients table is used to store the data of the pap smear patient. Meanwhile, the images table is used to store the images from the patient’s pap smear result. As depicted in Figure 4, one patient can have zero or more images, while one image must have one and only one patient.
4. Implementation Result

The system was implemented with Bahasa Indonesia as the displayed language because it is deployed to be used by clinics in Indonesia. The view presented in this paper is the English-translated version of the system. Figure 5 is the view of the login page after the implementation. The uploader is asked to provide their username and password to log into the system. If the username and password matched the credential saved in the database, then the view displayed in Figure 6 will be shown by the system. On the main page, the user can choose to upload data or edit the patient data.

![Login Page](image1)

![Main Page](image2)

Figure 5. (a) Login Page; (b) Main Page.

If the uploader chooses to upload data, a page as displayed in Figure 6 will be shown. On the upper part of the page, the uploader can upload multiple images or delete the wrongly uploaded images. On the lower-left part, the uploader can enter the patient data, which are the initial, age, date received, date responded, localization, clinical symptoms. On the lower-right part, the uploader is asked to provide the pap smear result.

![Upload Pap Smear Patient Data](image3)

Figure 6. Upload New Data Page.
Meanwhile, if the uploader chooses to edit patient data on the main page, the view depicted in Figure 7 will be displayed. Here, the uploader can find the patient whose data is going to be edited or deleted. If the uploader clicks Delete, the patient data will be deleted. Else, if the uploader clicks Edit, a page as displayed in Figure 8 will be shown. The view of this page is the same as the upload page, except that it shows the previously uploaded images and the previously entered data of the patient.

**Figure 7.** Page to Search Patient Data to be Edited.

**Figure 8.** Edit Patient Data Page.
5. Conclusion
This paper described the development process of a pap smear image recording system, which also stores the pap smear result. The design of this system allows it to be easily integrated into the current pap smear procedure. At the same time, the system collects the pap smear images that can be used to train an AI model that can be used as an automatic pap smear screening system in the future. After the images are collected, there will be a follow-up study to develop an AI model for an automatic pap smear screening system.

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