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MELANOMA AUTOMATED DETECTION SYSTEM INTEGRATED WITH AN EHR PLATFORM

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Early melanoma detection is vital for improved treatment outcomes and reduced mortality. This paper proposes integrating an automated melanoma detection system into the Electronic Health Record, offering benefits like seamless screening during routine medical visits, enhancing early lesion detection. The system's efficiency allows providers to focus on patient care, while real-time alerts ensure timely follow-up. Patient engagement promotes proactive skin health. Interoperability within the EHR facilitates comprehensive care, resulting in better outcomes, reduced costs, and proactive prevention.

Keywords: electronic health record, automated melanoma detection system, classification model

1. Introduction

Melanoma is a type of skin cancer that develops in the cells called melanocytes, which produce the pigment melanin responsible for the color of your skin, hair, and eyes. Melanoma occurs when these cells begin to grow uncontrollably and form malignant tumors. It is considered one of the most dangerous forms of skin cancer because it can spread (metastasize) to other parts of the body if not detected and treated early.

Melanoma is primarily caused by damage to the desoxyribonucleic acid (DNA) of skin cells due to exposure to ultraviolet (UV) radiation from the sun or tanning beds. However, genetics and family history can also play a role in increasing the risk of developing melanoma. Melanoma usually appears as a new mole or a change in an existing mole. It is essential to keep an eye on any moles or skin spots and look for the following signs that may indicate melanoma (using the ABCDE rule): A - Asymmetry: One half of the mole doesn't match the other half, B - Border: The edges of the mole are irregular, ragged, or not well-defined, C - Color: The mole has multiple colors, such as shades of brown, black, blue, red, or

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white, D - Diameter: The mole is larger than 6mm in diameter (about the size of a pencil eraser), but melanomas can be smaller, E - Evolving: The mole is changing in size, shape, or color over time. Treatment for melanoma depends on the stage of cancer and other factors. Early-stage melanomas that haven't spread may be treated with surgical excision, where the tumor and a margin of healthy tissue are removed. In advanced cases or when melanoma has spread to other parts of the body, treatments like immunotherapy, targeted therapy, radiation therapy, and chemotherapy may be used.

Thereupon early detection is crucial to increase the chances of survival. The solution lies in early detection and analysis of any skin lesions. Currently, this requires a visit to a doctor and numerous tests to establish a diagnosis, which can be time-consuming and challenging due to the decreasing number of specialists who can provide accurate diagnoses. The proposed solution in this work involves the early detection of melanoma using artificial intelligence, specifically neural networks, to assist clinicians in making accurate diagnoses in a simple and accessible manner for both patients and doctors. This is achieved by providing an image of the area with lesions. [1-4] Early detection of melanoma using an automated detection system is of utmost importance for several reasons:

- **Improved Prognosis:** Automated detection systems can help identify suspicious lesions at an early stage, allowing for timely intervention and improved patient outcomes.
- **Reduced Mortality:** Melanoma can be life-threatening if it progresses to an advanced stage and spreads to vital organs. Early detection and treatment can prevent the cancer from reaching this critical stage, reducing the risk of mortality.
- **Minimized Treatment Complexity and Cost:** Advanced melanoma often requires more aggressive treatments, including surgery, radiation, immunotherapy, and targeted therapy. Detecting melanoma early can lead to less invasive and less expensive treatment options, benefiting both patients and healthcare systems.
- **Promotion of Regular Skin Screening:** Automated detection systems can be integrated into routine healthcare check-ups, encouraging individuals to undergo regular skin screenings. Early detection tools can help raise awareness about the importance of monitoring moles and other skin abnormalities, leading to more proactive skin care practices.
- **Screening of High-Risk Populations:** People with a family history of melanoma, fair skin, excessive sun exposure, or a high number of moles are at higher risk. Automated detection systems can facilitate targeted screening of these high-risk populations, leading to the early identification of suspicious lesions.

- **Scalability and Efficiency:** Automated detection systems can analyze a large number of images quickly and accurately, making them ideal for screening a large population. This efficiency ensures that more individuals can be screened in a shorter period, enhancing the chances of early melanoma detection.
- **Assisting Healthcare Professionals:** Automated detection systems can act as a valuable tool for healthcare professionals, aiding in the identification of potential melanoma cases. By assisting medical practitioners, these systems can enhance diagnostic accuracy and reduce the likelihood of overlooking concerning lesions.
- **Patient Empowerment:** With automated systems that provide prompt feedback, patients can take proactive steps towards further evaluation and early treatment if needed. [5-10]

The goal of our research was to integrate an automated melanoma- detection module in an EHR like information system (IS). The chosen IS for this project is the Salesforce (SF) platform [11], a leading global provider of cloud-based software products in the field of Customer Relationship Management (CRM). Our research aimed to integrate an automated melanoma detection module into a SF-based EHR system. This customizable system allows seamless interconnection of modules, enabling a common interface for all medical institution processes. The proposed solution involves using SF to integrate an application for automatic medical image classification. The system's basic features include data records, real-time information, and customizable functionalities developed using JavaScript (JS) and APEX. Deployment in the production environment involves copying Salesforce metadata. To achieve our objectives, we began with a basic CRM environment, creating and managing image classification databases and developing the required automatic classifier workflow functionalities.

2. Materials and methods

In this chapter, we will describe the databases we used, the enviroment in which we developed the melanoma detection module and the model used for classification task.

2.1 Databases

The databases used to create the classification model are PH^2, MED-NODE, DermIS, ISIC 2018, and ISIC 2019. The PH^2 database contains 40 dermatoscopic images representing melanoma and 80 images non-melanoma. This database was specifically developed for algorithm testing in scientific research projects and was acquired at the dermatology hospital Pedro Hispano (Matosinhos, Portugal). These images were acquired in the same manner and have a resolution of 768 × 560 pixels. [12]

The ISIC (International Skin Imaging Collaboration) database contains 25,332 images of skin lesions and was developed for testing algorithms for melanoma detection. [13] The DermIS database contains the most comprehensive dermatological information available on the internet. In addition to images of almost all types of skin conditions and diagnoses, it provides differential diagnosis, case reports, and other additional information such as medical journals. This project is carried out in partnership with the University of Heidelberg and the Department of Dermatology (University of Erlangen). The database contains 500 images representing melanoma and 500 images non-melanoma. [14], [15]. MED-NODE contains 170 images (70 showing melanoma and 100 non-melanoma). [16].

2.2 Implementation Environment

We used and basic environment from SF. Usually if you are creating a information system, we need to work with several environments for production, testing and developing new functionalities. In this project, we are using a single environment (Figure 1) - the production environment, which comes with a standard configuration of standard objects for monitoring workflow and team activities.

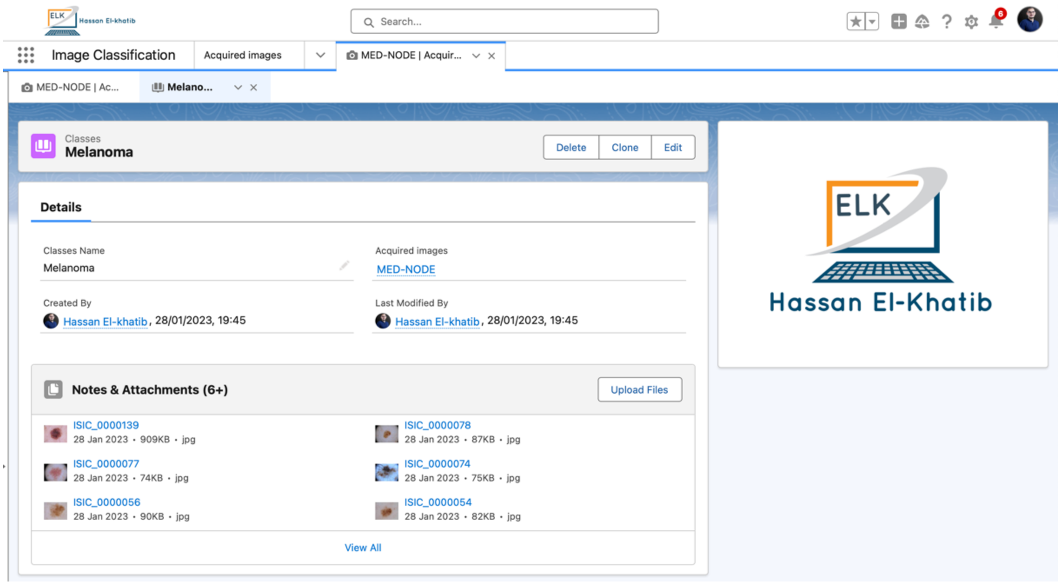

Fig. 1. The created enviroment – ELK

They come in several types:

- **FullCopy** - a faithful copy of the production environment. It contains all the data (information and records) and metadata from production.
- **PartialCopy** - a partial copy of the production environment, containing all the metadata and only a portion of the data (records and information). It is a suitable environment for testing.

- **Developer** - a limited development environment (200MB). Only metadata can be retrieved from production, not data.
- **Developer Pro** - a very similar testing environment to Developer, with larger storage capacity (1GB). It is a suitable environment for developing highly complex functionalities, such as integrations between multiple systems.

The initial step in implementing the melanoma detection module involves creating a customized working console, which provides access to workflow-specific objects. One such object is the image database, which can be stored using custom objects tailored to specific needs. We'll create two custom objects: "Acquired Images" to store image databases and "Classes" for non-melanoma and melanoma classes (Figure 2). The "Classes" object will be linked to the "Acquired Images" object through a Master-Detail Relationship, ensuring that child records are dependent on parent records. This relationship offers advantages like cascading deletions, inherited permissions, and unified reporting.

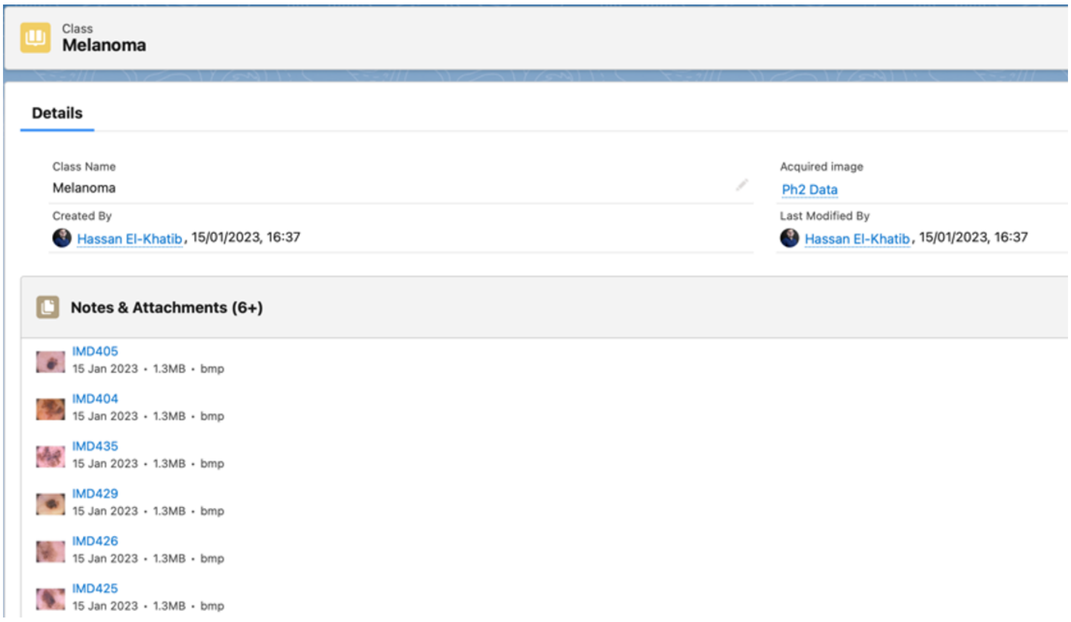

Fig. 2. The created objects for importing the databases in the EHR system

2.3 Classification Model

We reasearched several options for model creation including Google Teachable Machine (GT), Microsoft Azure Machine Learning (AML), Google Vertex AI (GVI). AML offers pre-trained CNN models like ResNet, VGG, and DenseNet for image classification, tailored to task requirements and databases. GVI employs diverse neural network architectures, encompassing CNNs, RNNs, transformer models, and DNNs, with the choice depending on the specific task or application at hand. For image classification, GVI offers support for various CNN models. [17]

AML and GVI both have complex structures and may incur additional costs due to their pay-as-you-go pricing model. Some integration scenarios may lack sufficient documentation or community resources. Integration with other platforms may require significant effort and tie users to the respective cloud ecosystems, potentially limiting flexibility. In AML, modifying parameters during training and validation might not be straightforward for a basic classification model. [18]. GT, a web-based tool designed for creating machine learning models, is highly versatile, offering good model accuracy. It seamlessly integrates with architectures using Java as the programming language. Notably, uploading images, training the model, and using it directly from the cloud are free of charge [19].

The new model in our project will be developed using GT, known for its versatility and flexible training parameters like learning rate, batch size, and epochs for optimal results. The models are trained and executed within web browsers. The creation process involves transfer learning, utilizing a pre-trained neural network, with user-relevant classes added as the final layer. For image classification, MobileNet is the chosen model. Once created, these models can be effortlessly integrated into JS-based applications. GT supports three model types: MobileNet for images, Speech Commands for audio, and PoseNet for pose estimation. The combination of GT, TensorFlow, and MobileNet provides a powerful and adaptable solution for seamless integration into web applications, ideal for this project's compatibility needs with SF. [19], [20] The process for creating the model is described in Figure 3.

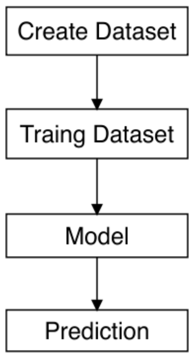

Fig. 3. Model creation steps

3. Experimental results

For the creation of the model, we used all the images from the mentioned databases (Table 2). We create models in every enviroment (GVI, GT and AML) using the databases mentioned in Table 1

Table 1

Used Databases and number of images

Database	No. of images Melanoma	No of images Non-melanoma
ISIC	1913	1843
DermIS	500	500
MEDNODE	70	100
PH^2	40	80
Total	2523	2523

Regarding the accuracy and F1 score the results are presented in Table 2 calculated with the formulas from Table 3.We trained models on each database individually and on all of them combined to have more examples. The best of them all was GVI.

Table 2

Results of training databases.

Browser based tool	**Database**	**Performance indicators**	
		Accuracy	**F1 Score**
Google Teachable Machine	DermIS	0.778	0.7592
	PH^2	0.900	0.8636
	MEDNODE	0.7647	0.7222
	ISIC	0.7602	0.7685
	Combined	0.7535	0.7372
Google Vertex AI	DermIS	0.9596	0.9608
	PH^2	0.8333	0.6667
	MEDNODE	0.7647	0.8333
	ISIC	0.7414	0.7115
	Combined	0.8327	0.8353
Microsoft Azure Machine Learning	DermIS	0.796	0.7984
	PH^2	0.900	0.8571
	MEDNODE	0.7907	0.7632
	ISIC	0.8236	0.8257
	Combined	0.7753	0.7869

Table 3

Expressions for the performance indicators

Performance Indicators	Formula
Precision	$\frac{TP}{TP+FP}$
Recall	$\frac{TP}{TP+FN}$
Accuracy	$\frac{TP+TN}{TP+FP+FN+TN}$
F1 score	$2\cdot\frac{Precision\cdot Recall}{Precision+Recall}=\frac{TP}{TP+\frac{1}{2}(FP+FN)}$

- TP = number of true positives (melanoma)
- FP = number of false positives (images predicted as melanoma that are non-melanoma)
- TN = number of true negatives (non-melanoma)
- FN = number of false negatives (images predicted as non-melanoma that are melanoma)

Even the fact that GVI has better accuracy, from the integration point of view, we will choose GT to create the model for the melanoma detection module using PH^2, MED-NODE, DermIS, ISIC 2018, and ISIC 2019 databases for training. Parameters used for training and validation were 400 epochs with a batch size of 512 and a learning rate of 0.001. The training progress can be seen in Figure 4a and the confusion matrix in Figure 4b. The model is uploaded to the Google Cloud, and a URL is generated for the melanoma detection module that will be included in a JavaScript code for integrating the model into the melanoma detection module (programming language compatible with the one SF uses).

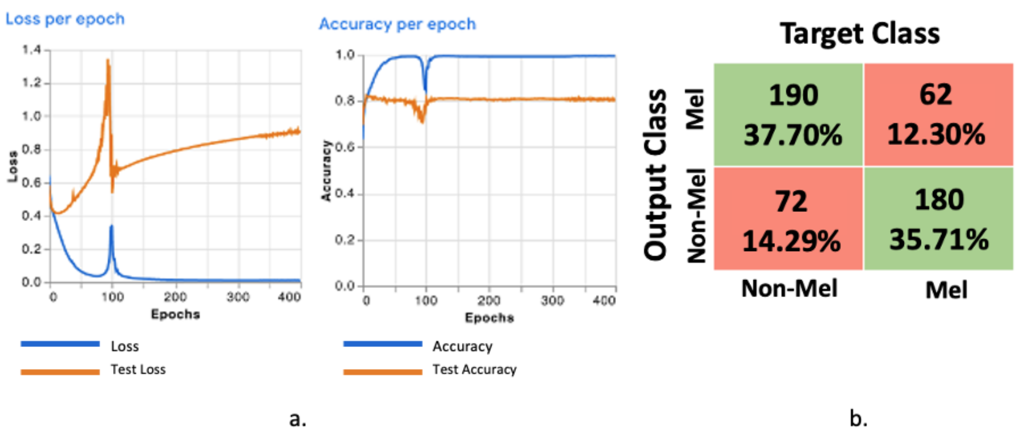

Fig. 4. a. Training progress, b. Confusion matrix for GT.

The code arguments are:

- Model (file containing the model's topology in JSON format)
- Weights (file containing the model's weights)
- Metadata (file containing the model's labels and additional information)

To load the model into SF, we will use VisualForcePage (VFP) that is similar to a standard web page but includes functionality to access, display, and update data. VFP pages can be referred to and invoked through a unique URL, similar to a traditional web server. Visualforce markup can be freely mixed with HTML markup, CSS styles, and JS libraries, offering flexibility for implementing an application's interface. The advantage of VFP is that these pages can be created and modified using SF APIs, allowing for a variety of external tools. The results are presented in Figure 5. Using the computer's or smartphone camera, the area of interest can be visualized, and real-time detection is performed.

a. b.

Fig. 5. Predictions of the automated melanoma detection module. a. Non-melanoma, b. Melanoma

6. Conclusions

In conclusion, early detection of melanoma plays a crucial role in improving treatment outcomes, reducing mortality, lowering healthcare costs, and promoting overall public health. It empowers individuals to take charge of their skin health, leading to timely interventions and potentially life-saving measures.

In this paper we implemented an automated detection sistem for melanoma integrated into an EHR system using the SalesForce platform as an information system, Google Teachable Machine for creating the necessary model for the melanoma detection system and the main contribution is the integration made between SalesForce and Google Teachable Machine. The integration of an automated melanoma detection system into an EHR system offers several significant benefits for the early detection of melanoma:

- **Seamless Screening Process:** By integrating the automated detection system directly into the EHR, healthcare providers can seamlessly incorporate melanoma screening as a routine part of patients' medical visits. This ensures that individuals undergo regular skin assessments, increasing the chances of detecting suspicious lesions at an early stage.
- **Efficient Workflow:** The automated detection system streamlines the screening process, making it more efficient for healthcare professionals. The system can automatically analyze images of moles or skin lesions, flagging potentially concerning cases for further examination by medical experts. This

reduces the burden on healthcare providers, allowing them to focus on more critical aspects of patient care.

- **Real-Time Alerts:** An integrated automated system can provide real-time alerts to healthcare professionals if it detects any suspicious lesions during routine patient visits or when reviewing medical records. This prompt notification enables timely follow-up and appropriate intervention.
- **Enhanced Accuracy:** Automated detection systems leverage advanced algorithms and machine learning to analyze skin images and identify potential melanoma signs accurately. These systems can help reduce human errors and improve diagnostic accuracy, ensuring that no potential cases go unnoticed.
- **Patient Engagement and Education:** EHR systems with integrated automated melanoma detection can engage patients in their own healthcare. Patients can view the results of the screening process, understand potential risk factors, and be more proactive about their skin health.
- **Monitoring High-Risk Patients:** EHRs often contain valuable patient data, including risk factors for melanoma. By using an automated detection system integrated into the EHR, healthcare providers can monitor high-risk patients more effectively and ensure they receive regular screenings and follow-up evaluations.
- **Data-Driven Decision Making:** An integrated system can accumulate data from multiple screenings and patient histories, enabling data-driven decision making and trend analysis. This data can help identify patterns and risk factors associated with melanoma, potentially leading to more targeted prevention and intervention strategies.
- **Population Health Management:** The aggregated data from the automated melanoma detection system can contribute to population health management efforts. Healthcare institutions can identify trends in melanoma prevalence, target specific at-risk populations, and allocate resources more effectively.
- **Interoperability and Continuity of Care:** Integration within the EHR ensures that the results of melanoma screenings are accessible to all authorized healthcare providers involved in a patient's care. This facilitates better communication and continuity of care, avoiding redundant screenings and ensuring a comprehensive approach to patient management. [20-26]

The implemented solution can be used on various types of medical images. The next steps for improving the solution include replacing Visualforce pages with LWC (Lightning Web Component), which is a more challenging development solution. However, the advantage of LWC is that the application utilizes browser resources rather than the server's resources. Another improvement would be to modify the information retrieval method. While the video solution is suitable for skin images, if the classifier is used on other types of images acquired through equipment (X-ray, MRI, etc.), the information retrieval method needs to be adjusted. In conclusion, the integration of an automated melanoma detection system into an EHR system not only improves the efficiency and accuracy of melanoma screening but also empowers patients to take a more active role in their skin health. The early detection of melanoma through such a system can significantly impact patient outcomes, reduce healthcare costs, and promote proactive preventive measures.

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