Comparative analysis of web-based machine learning models

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Abstract: This paper presents a comparative analysis of web-based machine learning models, specifically examining Google Vertex AI, Google Teachable Machine, Azure Machine Learning and Salesforce Einstein Vision. The objective is to assess their suitability for integration into a medical information system as a classification module for medical images. The comparative evaluation considers factors such as model accuracy, ease of integration and scalability. The findings aim to guide the selection of an optimal machine learning solution for enhancing the capabilities of medical image classification within a healthcare context.

Keywords: Healthcare, Web-based Machine Learning Models, Decision Support, Classification Module, Medical Image Analysis.

Analiza comparativă a modelelor de învățare web-based

Rezumat: Acest articol prezintă o analiză comparativă a modelelor de învățare automată web-based, examinând în mod specific Google Vertex AI, Google Teachable Machine, Azure Machine Learning și Salesforce Einstein Vision. Scopul este de evalua aceste sisteme în vederea integrării acestora într-un sistem informatic medical ca modul de clasificare pentru imagini medicale. Evaluarea comparativă ia în considerare factori precum acuratețea modelului, ușurința de integrare și scalabilitatea. Concluziile urmăresc să ghideze selecția unei soluții optime de învățare automată pentru îmbunătățirea capacităților de clasificare a imaginilor medicale într-un context de asistență medicală.

Cuvinte cheie: sănătate, modele de învățare automată web-based, suport decizional, modul de clasificare, analiză de imagini medicale.

1. Introduction

In the dynamic landscape of healthcare, the integration of advanced technologies is essential for enhancing diagnostic capabilities, optimizing workflows, and ultimately enhancing patient outcomes. One notable enhancement to medical information systems is the inclusion of an automated classification module powered by machine learning, representing a pivotal advancement in leveraging artificial intelligence (AI) for the analysis and interpretation of medical images (Crăciun, 2023).

The advantages of integrating such an automated classification module into a medical information system are multifaceted. Firstly, it provides a robust solution for managing the increasing volume and complexity of medical imaging data. With healthcare institutions facing a surge in diverse imaging modalities and datasets, automating image classification tasks becomes crucial in relieving the workload on healthcare professionals, allowing them to prioritize patient care (Todor et al., 2015).

Furthermore, the precision and efficiency offered by machine learning algorithms significantly enhance diagnostic accuracy. Automated classification systems can swiftly and accurately categorize medical images, assisting clinicians in identifying patterns, anomalies and potential disease indicators. This expedites the diagnostic process and enhances the overall reliability of medical interpretations (Singh et al., 2022).

Additionally, the integration of such a module establishes a foundation for standardized and consistent analysis across healthcare settings. By minimizing the subjectivity associated with manual image interpretation, automated classification ensures a more uniform and reproducible diagnostic approach, promoting better collaboration among healthcare professionals and facilitating

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seamless exchange of medical information. Moreover, as healthcare systems transition towards a patient-centric model, the incorporation of automated classification aligns with the objective of delivering personalized and timely care. Rapid analysis of medical images enables faster decision-making, leading to prompt initiation of appropriate treatments and interventions (Tîrziu et al., 2018).

In this study, a comparative analysis of web-based machine learning models was conducted with a specific focus on Google Vertex AI, Google Teachable Machine, Azure Machine Learning, and Salesforce Einstein Vision. The goal is to assess the capabilities of these platforms and identify the most suitable candidate for integration as a classification module in a medical information system. By harnessing the potential of automated classification, significant advancements in the efficiency, accuracy, and overall quality of healthcare diagnostics are anticipated (Ștefan et al., 2024).

2. Materials and methods

Diverse datasets are employed to construct models for both classifying ocular images and images featuring skin lesions, aiming for a comprehensive representation. For ocular pathologies, datasets such as ORIGA, Messidor, EyePacs, HRF, and Ponderas were utilized, while skin pathologies were addressed with ISIC, DermIS, MED-NODE, PH2. The models were designed with dual targets (healthy or diseased) as well as three or four targets (healthy or one of the investigated pathologies). Ocular pathology images were obtained through ocular fundoscopy, while skin pathology images were captured using a camera. The model that exhibited superior performance in terms of accuracy, F1 score, and adaptability to external platforms across various medical image databases would be selected.

2.1. Databases

For ocular image classification several databases were used such as:

ORIGA (Online Retinal Fundus Image Dataset for Glaucoma Analysis and Research) – is a public database containing 168 color fundus images of the posterior pole with glaucoma and 482 healthy eye images. The images were obtained as part of a screening initiative known as the Singapore Malay Eye Study (SiMES), administered by the Singapore Eye Research Institute (SERI) (Zhang et al., 2010).

Messidor – is a database for diabetic retinopathy, consisting of 1200 retinal images, labeled by experts. Out of these, 800 were acquired with dilated pupils. The images were obtained through a screening program in Switzerland, investigating diabetic patients aged between 25-90 years. This research program was funded by the French Ministry as part of the Techno-Vison 2004 program (Messidor – ADCIS, n.d.).

EyePacs – A database of diabetic retinopathy images, comprising 35,126 entries, is accessible on Kaggle, sourced from screening programs (Data Analysis, 2020).

Cataract Dataset from Kaggle – that containes 601 images that contain different pathologies like cataract, retina disease, glaucoma and normal eyes (Cataract Dataset, 2019).

HRF (The High-Resolution Fundus Image Database) - comprises 15 images each of healthy eyes, glaucoma-affected eyes, and eyes with diabetic retinopathy. It is made available by the CS5 Laboratory at the Department of Ophthalmology of the Friedrich-Alexander University Erlangen-Nuremberg and the Department of Biomedical Engineering at Brno University of Technology (Erlangen-Nürnberg, n.d.).

Database of Images with Multiple Pathologies (cataract, glaucoma and diabetic retinopathy). Available on Kaggle, this database contains 601 images divided into 5 classes (Diabetic Retinopathy Detection - Kaggle, n.d.) and additionally, a set of images was obtained from Ponderas Academic Hospital, containing 32 images of patients with glaucoma and 34 images of patients without pathologies.

RIM-ONE – a database containing retinal images obtained from ocular fundus images, with 200 glaucoma images and 255 without pathologies (Fumero et al., 2011; RIM-ONE Dataset, n.d).

For skin image classification several dabases were used such as:

ISIC (International Skin Imaging Collaboration) – contains 93,083 images of skin lesions developed for testing algorithms for melanoma detection, with 71,372 for training and 21,711 for testing. ISIC is the largest public database of dermoscopic images for skin lesions, obtained from various institutions worldwide from over 2000 patients. The goal of ISIC is to promote the creation of the most efficient system for detecting skin lesions (ISIC / International Skin Imaging Collaboration, n.d.).

DermIS - This database stands as one of the most extensive collections of dermatological images encompassing nearly all varieties of skin conditions. The images were obtained through a collaborative project involving the University of Heidelberg and the Department of Dermatology at the University of Erlangen. Comprising 500 images depicting melanoma and 500 images of non-melanoma conditions, the database offers a diverse representation of skin ailments (DermIS, n.d.).

MED-NODE - Comprising a total of 170 images, this dataset includes 70 images exhibiting melanoma and 100 images without any abnormalities. Acquired by the Department of Dermatology at the University Medical Center Groningen (UMCG), these images served as the dataset for training and testing the MED-NODE system, aimed at detecting cancer in macroscopic images (Giotis et al., 2015).

PH^2 - Comprising 40 dermoscopic images depicting melanoma and 80 images devoid of pathologies, this database was created expressly for algorithm testing in scientific research initiatives. Acquired at the dermatology hospital of Pedro Hispano Hospital in Matosinhos, Portugal, these images were obtained using the same method and have a resolution of 768 × 560 pixels (Mendonca et al., 2013).

The images from the mentioned databases have been categorized by pathology. Table 1 shows the total number of images that will be used for testing the web-based tools. Data augmentation techniques such as flipping, resizing, cropping, and adjusting brightness and contrast were employed to increase the number of images (Ștefan et al., 2024).

Table 1. Classes and the number of images based on pathology.

Image Class	Number of images
Ocular pathologies	
Glaucoma	1150
Cataract	1176
Diabetic retinopathy	1006
Normal	1299
Skin pathologies	
Melanoma	2463
Normal	2463
Actinic keratosis	2166
Seborrheic keratosis	2764
Basal cell carcinoma	2764

2.2. Methodology for performance evaluation

To assess the automatic classification models, accuracy and the F1 score were employed, considering their consideration of both false negatives and false positives. Examples illustrating the performance indicators are provided in Table 2.

Table 2. 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; FP = number of false positives; TN = number of true negatives; FN = number of false negatives.

• **Accuracy** - is a frequently utilized metric for assessing the overall effectiveness of a pathology detection system. It computes the proportion of accurately classified data (in this instance, images) as either pathology or pathology-free cases.

• **F1 Score** - is a metric that merges both precision and recall. It considers both false positives (FP) and false negatives (FN) and provides a balanced measure of a model's performance. Higher F1 scores indicate better performance in terms of both precision and recall.

• **Sensitivity/Recall** - Sensitivity, also referred to as recall or true positive rate, gauges the ratio of actual pathology cases correctly identified by the system. It focuses on minimizing false negatives (FN) and is particularly important in medical applications to avoid missing pathology cases.

• **Specificity** - Specificity measures the proportion of pathology free cases correctly identified as such by the system. It focuses on minimizing false positives (FP) and is essential to reduce unnecessary invasive procedures of diagnosis or false alarms. (El-khatib et al., 2023; El-khatib et al., 2024; Esteva et al., 2017; Ștefan et al., 2024).

In the prior researchs (El-khatib et al., 2023; El-khatib et al., 2024), web-based models with the same performance metrics were examined concentrating exclusively on a single pathology as opposed to a system relying on the combination of decisions from multiple neural networks. Due to the inability to integrate the decision fusion system, the expansion of the research in order to encompass multiple pathologies for web-based tools was considered.

2.3. Web-based models

Web-based machine learning models offer a dynamic and intelligent dimension to applications, enabling them to adapt, learn and provide personalized experiences. These models harness the power of data to make predictions, automate processes, and enhance decision-making within the web environment. Whether employed for recommendation systems, natural language processing, image recognition, or predictive analytics, the utilization of machine learning on the web opens up a realm of possibilities for innovation and efficiency. This introduction delves into the profound impact of web-based machine learning models, exploring their diverse applications and the pivotal role they play in shaping the future of interactive online experiences.

Google Vertex AI is a development environment for applications that allows the implementation and management of computer vision applications, building and training custom models and storing them in the cloud. After the model is trained, it can be deployed to an endpoint for integration into an external platform. Uploading images for model construction and training costs several hundred euros per month after exhausting credits.

Google Vertex AI leverages a range of neural network architectures, including, but not limited to, CNNs, RNNs, and DNNs. The specific neural network architecture used by Google

Vertex AI can vary depending on the task or application at hand. Google Vertex AI supports a variety of CNN models tailored to image classification tasks (Vertex AI, n.d.). Among the commonly used CNN models within GVI are EfficientNet that is a collection of CNN models that showcase cutting-edge performance in image classification tasks while efficiently managing model size and computational resources, ResNet, a widely recognized CNN architecture, stands out for its deep structure and employs residual connections to address the vanishing gradient problem, allowing the training of highly complex networks. Inception models distinguish themselves through the use of Inception modules, which facilitate efficient feature extraction at various scales. On the other hand, MobileNet is specifically designed for mobile and embedded devices, offering a lightweight CNN architecture that strikes a favorable balance between model size and accuracy by implementing depthwise separable convolutions (El-khatib et al., 2023; El-khatib et al., 2024; Howard et al., 2017; Ștefan et al., 2024; Vertex AI, n.d.). The platform's structure is illustrated in Figure 1.

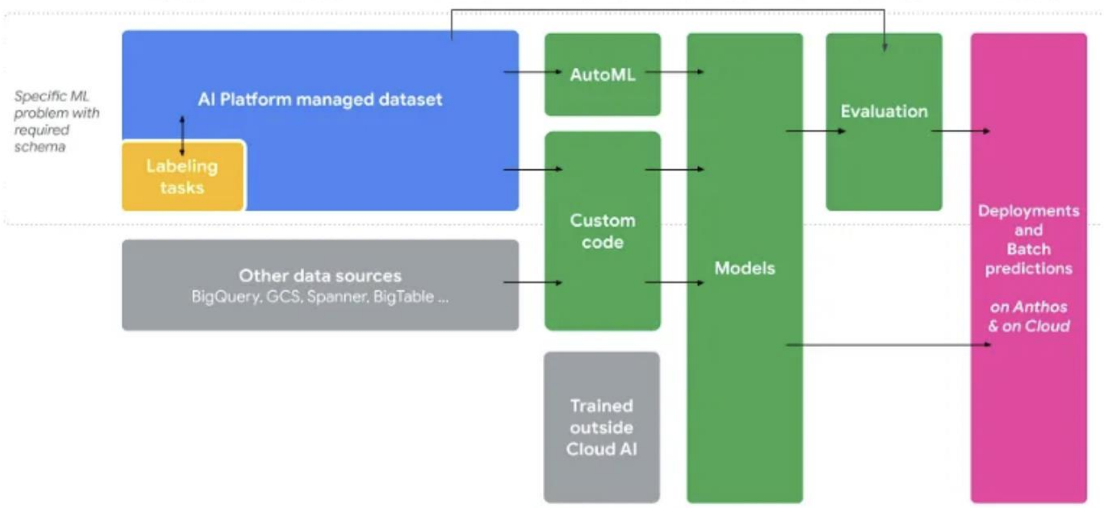

Figure 1. Google Vertex AI Arhitecture (Vertex AI, n.d.)

Google Vertex AI stands out as a robust platform for the development, implementation and management of machine learning models, offering a diverse set of advantages. The platform provides a unified environment, consolidating various machine learning tools and services, streamlining the entire machine learning lifecycle from data preparation to deployment. With powerful AutoML capabilities, Vertex AI automates key aspects of the machine learning process, accelerating model development and ensuring accessibility for users of different experience levels. It includes a variety of prebuilt and customizable models for common use cases, such as image classification and text recognition, allowing developers to harness advanced machine learning capabilities rapidly. Leveraging Google Cloud's infrastructure, Vertex AI enables efficient scaling of machine learning tasks, making use of potent computational resources for large-scale model training and predictions with extensive data and complex models. The platform supports efficient data labeling and annotation, crucial in training machine learning models across various data types. After training, Vertex AI facilitates easy deployment with tools for versioning, monitoring, and updating deployed models. It is deeply integrated with other Google Cloud services and tools, simplifying utilization for data storage, processing, analysis, and data visualization. Vertex AI offers customization options, allowing the creation of custom models with flexibility in architecture, algorithms, and optimization techniques. Google Cloud ensures robust security features to safeguard data and models. While these advantages enable efficient machine learning solutions, potential drawbacks must be considered when integrating Vertex AI into another platform. These include a learning curve, consumption-based pricing, platform dependency, integration effort, infrastructure management, and the need for familiarity with Google Cloud services. These considerations are crucial for successful integration, keeping in mind the achieved accuracy of 90% for ocular pathologies and 83% for skin pathologies. Despite the model's good accuracy, integration with other APEX-based platforms may pose challenges. (El-khatib et al., 2023; El-khatib et al., 2024; Vertex AI, n.d.).

Google Teachable Machine functions as an online platform designed for creating machine learning models, utilizing TensorFlow through the TensorFlow.js libraries, which is a FOSS (Free and Open Source Software) resource for machine learning and artificial intelligence (AI). Fundamentally a pre-initialized CNN serves as the groundwork, with user-defined classes integrated as the final layer. These web-based models are specifically engineered to undergo both training and operation directly within a web browser, employing techniques such as transfer learning. The designated model for image classification is MobileNet, seamlessly integrating resulting models into JavaScript-based applications.

Google Teachable Machine offers three distinct model types tailored for various classifications: MobileNet, Speech Commands and PoseNet for imagine, audio and video classification (El-khatib et al., 2023; El-khatib et al., 2024; Teachable Machine, n.d.). GT offers numerous advantages, including a friendly user interface enabling users to develop and train machine learning models even without coding expertise, making it accessible to a wide range of users. GT facilitates swift prototyping, which is essential for exploring diverse ideas and testing concepts in research endeavors. With support for image, audio, and pose inputs, GT enables the development of models tailored to specific requirements. Leveraging transfer learning accelerates the training phase, allowing for efficient model generation with minimal data volume. Models produced in GT can be exported as TensorFlow, TensorFlow Lite, TensorFlow.js, p5.js, keras.h5 models, seamlessly integrated into web applications (including Android and Coral) without the need for complex infrastructure (El-khatib et al., 2023; El-khatib et al., 2024; Ștefan et al., 2024).

Incorporating GT into another web-based platform might lead to reliance on Google's infrastructure and ecosystem, potentially constraining flexibility for future transitions or modifications. Moreover, GT, tailored for straightforward, small-scale machine learning initiatives, might not be suitable for larger applications with substantial computational needs. Although Google offers documentation and resources for Teachable Machine, the level of support and available resources might be constrained in comparison to more prevalent machine learning frameworks. Since GT predominantly functions as a web-based tool, implementing it offline or integrating it with non-web-based platforms may necessitate additional development work to tailor the Teachable Machine model accordingly. While its streamlined workflows offer benefits for quick prototyping, they may not provide the same degree of control found in more intricate frameworks. This often requires additional development work outside of GT for advanced customization or model optimization. When contemplating integration with another platform, it's important to acknowledge certain limitations. While GT prioritizes accessibility, its customization options may not match those of more sophisticated machine learning frameworks.

Despite these considerations, in the context of the project's goal, by incorporating an image classification model, GT maintains its versatility, affordability and seamless integration into platforms utilizing APEX as the programming language. (Teachable Machine, n.d.; El-khatib et al., 2023; El-khatib et al., 2024; Ștefan et al., 2024).

Azure Machine Learning offers a versatile range of pre-trained CNN models, including ResNet, VGG, and DenseNet, tailored for image classification. The choice of model is contingent upon specific task requirements and the utilized database. The workflow initiates with file upload, triggering Azure functions. These functions sequentially invoke the Azure Computer Vision API to analyze the uploaded image. Subsequently, the Azure functions retain the API response, encompassing classification results and image metadata, which can be visualized through a web or mobile interface. Azure Machine Learning is distinguished by several advantages, positioning it as a robust platform for developing, implementing, and managing machine learning solutions. Firstly, AML prioritizes ease of use and productivity, offering a user-friendly interface and tools that streamline the entire machine learning process, accommodating both visual and code-based preferences. Secondly, its integrated environment seamlessly connects with other Azure services, establishing a comprehensive ecosystem that minimizes data movement and simplifies the overall workflow. Leveraging Azure's cloud infrastructure, AML ensures scalability, allowing experiments and models to scale as needed for extensive training and effective prediction management. The inclusion of AutoML capabilities automates various aspects of the machine learning process, making it more accessible to non-experts. AML supports a diverse set of tools, catering to various programming languages, frameworks, and tools, including popular open-source libraries like TensorFlow, PyTorch, and scikit-learn (Azure Machine Learning - ML as a Service / Microsoft Azure, n.d.; El-khatib et al., 2023; El-khatib et al., 2024).

Moreover, AML facilitates model deployment and management through uncomplicated options such as Docker containers and the Azure Kubernetes Service (AKS). The platform provides tools for versioning, monitoring, and updating deployed models, ensuring seamless integration into production environments. Real-time monitoring allows continuous enhancement of deployed model performance based on new data and pattern changes. Azure's robust security features address data and model safeguarding, aligning with compliance requirements. AML also supports customizable workflows tailored to specific requirements and hybrid scenarios, allowing the utilization of on-premises resources while integrating with cloud-based services. While these advantages underscore AML's efficacy for data scientists, developers, and organizations, potential challenges arise when integrating it into another platform. These include the platform's complexity, operating on a consumption-based pricing model, potential platform dependency, integration effort requirements, infrastructure management demands, and considerations regarding support and documentation.

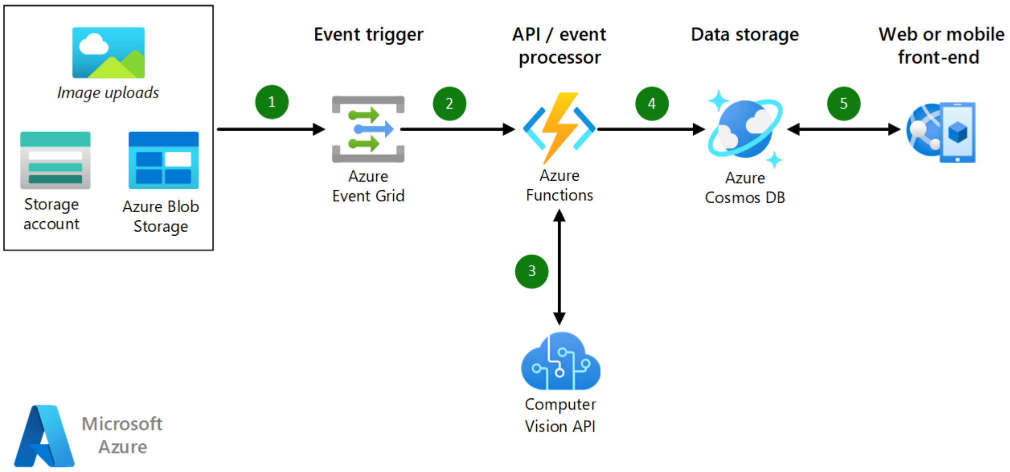

Figure 2. The workflow of Azure Machine Learning
(Azure Machine Learning - ML as a Service / Microsoft Azure, n.d.)

However, these disadvantages do not inherently restrict AML's capabilities but highlight aspects to be considered during integration. AML can be integrated with Salesforce in reverse, processing information from Salesforce in Azure. Integrating an external classification model with Salesforce involves invoking the model in the Salesforce application, with Azure Machine Learning utilizing Python as the programming language, though presenting an architecture incompatible with Salesforce. Additionally, the loading of images for model construction and training can be undertaken without cost by creating a student account at UPB.

Einstein Vision and Language Model Builder, an application designed for automated image analysis, categorizes images by training a model on a dataset divided into classes. Developed using programming languages such as APEX, Java, Scala, and Node, the Einstein Vision application employs a deep learning model based on the programming language API. This enables access to pre-trained classifiers or the training of custom classifiers to address various practical scenarios in the realm of Computer Vision. In addition to image classification, the EV package facilitates object detection, OCR (Optical Character Recognition), Sentiment analysis (predicting sentiments from written feedback), and Intent categorization (understanding user objectives from unstructured texts). The architecture of the Einstein Vision application within Salesforce involves a Managed Package, installed in the Salesforce production environment through a multi-step process, including creating an account, generating an activation key, creating a remote site, and configuring the application (Einstein Vision and Language Model Builder: User Guide, n.d.; El-khatib et al., 2023; El-khatib et al., 2024; Malmqvist, 2021).

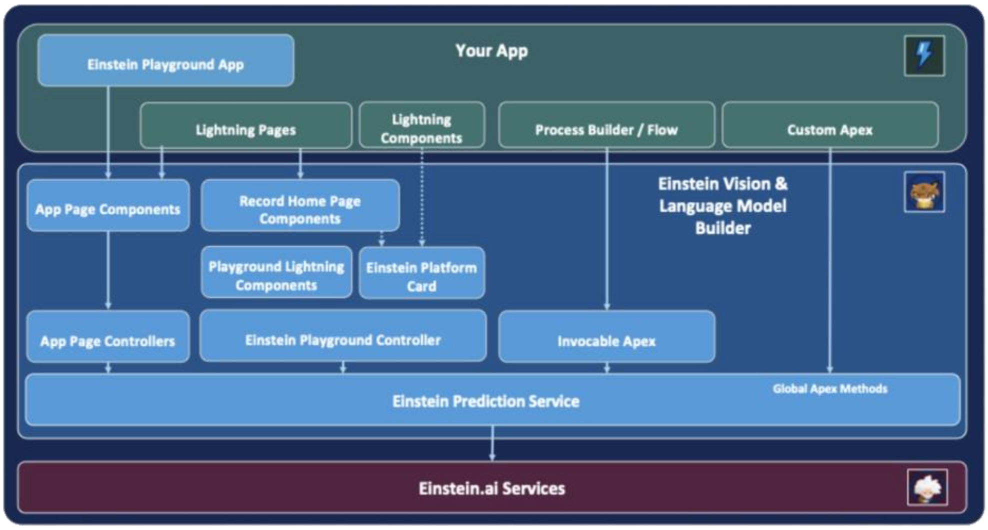

Figure 3. Einstein Vision Arhitecture (Einstein Vision and Language Model Builder: User Guide, n.d.)

Salesforce Einstein incorporates diverse neural network architectures, including Convolutional Neural Network for image recognition due to their effectiveness in extracting features from images and their widespread use in computer vision tasks. Recurrent Neural Network for sequential data processing like natural language, and Long Short-Term Memory neural networks for capturing long-term dependencies in sequential data. RNNs and LSTM networks, are employed for processing sequential data like natural language because of their ability to capture the temporal dependencies within such data. This combination of neural network architectures allows Salesforce Einstein to leverage the strengths of each model type for their respective tasks, resulting in more accurate and versatile data processing capabilities.

Although specific details of the neural network architectures and training process used by Salesforce Einstein Vision are not publicly disclosed, extensive research reveals several advantages of the platform. Powered by advanced deep learning algorithms and artificial intelligence technologies, Salesforce Einstein Vision excels in image recognition, object detection, and visual data analysis. Its seamless integration with the Salesforce ecosystem, automated data preparation capabilities, support for mobile integration, continuous learning, enhanced automation, and scalability within the Salesforce cloud infrastructure make it a potent tool for implementing image recognition and AI capabilities. However, considerations for customization limitations, tight integration with the Salesforce ecosystem, potential additional costs, suitability for complex tasks, scalability constraints, and integration limitations should be taken into account when evaluating Salesforce Einstein Vision for specific projects and contexts. (El-khatib et al., 2023; El-khatib et al., 2024; Malmqvist, 2021).

Table 3 provides a concise overview of key features and characteristics of four prominent machine learning platforms: Google Vertex AI, Google Teachable Machine, Microsoft Azure Machine Learning, and Salesforce Einstein Vision. The comparison encompasses elements such as the main objective, user proficiency level, supported model types, ease of training, deployment choices, compatibility with cloud services, adaptability and customization options, beginner-friendly interface, advanced functionalities, and pricing structures.

Table 3. Comparison of Machine Learning Platforms

Feature	Google Vertex AI	Google Teachable Machine	Microsoft Azure ML	Salesforce Einstein Vision
Primary Purpose	End-to-End ML Platform	Simplified ML for Beginners	Comprehensive ML Platform	AI-Powered Image Recognition
User Skill Level	Advanced Users/Developers	Beginners/No Coding	Intermediate to Advanced	Business Users/Developers

Model Types Supported	Wide Range	Image Classification	Wide Range	Image Classification
Training Ease	Requires ML Expertise	User-Friendly Interface	Moderate Learning Curve	User-Friendly Interface
Deployment Options	Cloud-based	Web Browser	Cloud-based	Cloud-based
Integration with Cloud Services	Google Cloud Platform	Google Cloud Platform	Microsoft Azure Services	Salesforce CRM
Customization and Flexibility	High	Limited	High	Limited
Ease of Use for Beginners	Not Ideal for Beginners	Very User-Friendly	Requires Learning Curve	User-Friendly
Advanced Features	Hyperparameter Tuning,	Limited Advanced Features	Automated Machine Learning	Integration with CRM Data
Pricing Model	Pay-as-You-Go	Free	Pay-as-You-Go	Subscription-Based

3. Experimental results

The models underwent training using default parameters specific to each Vertex AI and Azure Machine Learning allows users to train AutoML image classification models, where the model architecture and hyperparameters are automatically optimized by the service. The user simply needs to provide the training image dataset, and the plarform will handle the model training and optimization process. So, in summary, these two platforms leverage state-of-the-art CNN architectures for image classification, with the specific model details being automatically determined and optimized by the service based on the provided training data. In the case of Google Teachable Machine, the training process followed default settings: 50 epochs, a batch size of 16, and a learning rate set at 0.001.

The outcomes, detailed in Table 4, were computed using the formulas outlined in Table 2, and the composition of each database is summarized in Table 1. During the training process, 80% of the images were employed, with 10% allocated for validation and an additional 10% reserved for testing. In Figures 4 and 5 are presented the confusion matrices obtained in the testing phase and the results in terms of accuracy and F1 score are presented in Table 4. Notably, Google Vertex AI demonstrated the highest performance, with Google Teachable Machine ranking as the second-best performer.

Figure 4. The confusion matrices obtained after testing the web-based models on databases with ocular pathologies

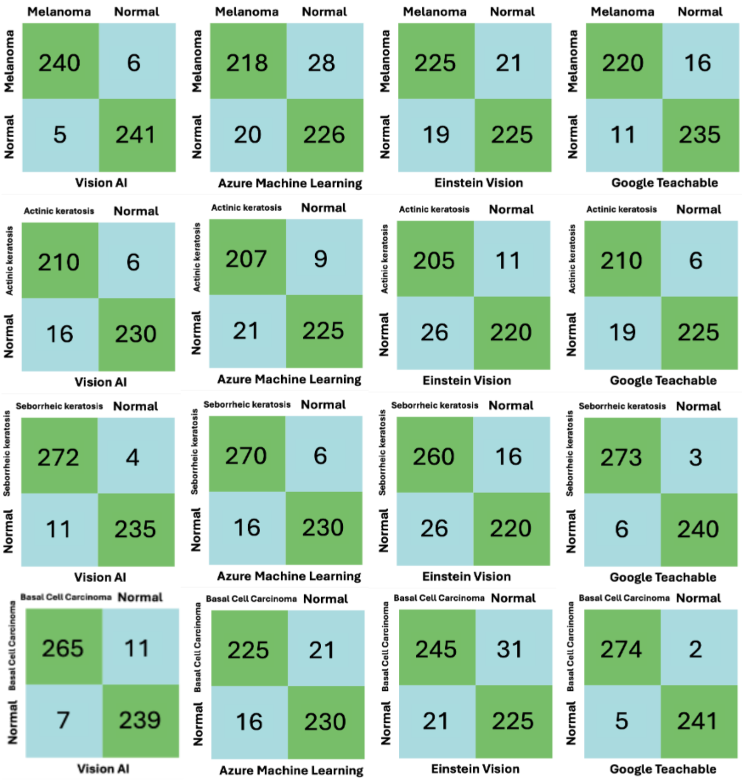

Figure 5. The confusion matrices obtained after testing the web-based models on databases with skin lesions

Table 4. The precision of the models evaluated

Web-based tool	Disease	Accuracy	F1 score
Azure Machine Learning	Glaucoma	0.9631	0.9630
	Cataract	0.9024	0.9024
	Diabetic retinopathy	0.9651	0.9645
Google Teachable	Glaucoma	0.9713	0.9712
	Cataract	0.9675	0.9674
	Diabetic retinopathy	0.9476	0.9462
Google Cloud – Vision AI	Glaucoma	0.9836	0.9836
	Cataract	0.9878	0.9878
	Diabetic retinopathy	0.9825	0.9822
Einstein Vision	Glaucoma	0.9188	0.9179
	Cataract	0.874	0.8735
	Diabetic retinopathy	0.9083	0.9080
Azure Machine Learning	Melanoma	0.9024	0.9024
	Actinic keratosis	0.9351	0.9352
	Seborrheic keratosis	0.9579	0.9576
	Basal cell carcinoma	0.9291	0.9290
Google Teachable	Melanoma	0.9451	0.9451
	Actinic keratosis	0.9457	0.9456
	Seborrheic keratosis	0.9828	0.9827
	Basal cell carcinoma	0.9866	0.9865
Google Cloud – Vision AI	Melanoma	0.9776	0.9776
	Actinic keratosis	0.9524	0.9523
	Seborrheic keratosis	0.9713	0.9711

	Basal cell carcinoma	0.9655	0.9654
Einstein Vision	Melanoma	0.9184	0.9184
	Actinic keratosis	0.9199	0.9198
	Seborrheic keratosis	0.9195	0.9191
	Basal cell carcinoma	0.9004	0.9002

The research and findings showcased in this paper build upon previous studies conducted in (El-khatib et al., 2023; El-khatib et al., 2024), and represent the preliminary stage in the development of a medical information system incorporating an automated classification module designed specifically for skin and ocular pathologies (Ștefan et al., 2024). Subsequent to the evaluation of four web-based tools, the automated module was seamlessly integrated into an EHR system.

4. Conclusions

In conclusion, after a thorough evaluation of various machine learning platforms, the decision has been made to integrate the Google Teachable Machine model into our medical information system. The selection is rooted in the platform's user-friendly interface, making it particularly suitable for beginners and users with limited coding experience. This aligns seamlessly with our goal to enhance accessibility and usability within the medical context.

Furthermore, the compatibility of Google Teachable Machine with Salesforce and Apex, as highlighted during the assessment, played a pivotal role in the decision-making process. The seamless integration capabilities with Salesforce's CRM and Apex programming language will facilitate a streamlined implementation of the machine learning model into our existing medical information system. This integration not only ensures a cohesive workflow but also leverages the power of machine learning to enhance our system's capabilities in image classification, particularly in the medical domain. By selecting Google Teachable Machine, a harmonious blend of user-friendly design, powerful machine learning capabilities, and seamless integration with the existing Salesforce infrastructure is anticipated. This decision underscores the commitment to providing a technologically advanced and user-centric medical information system that meets the evolving needs of healthcare professionals and practitioners.

As the dynamic landscape of healthcare is navigated, the integration of advanced technologies, particularly machine learning-based automated classification modules, emerges as a pivotal innovation for enhancing diagnostic capabilities and transforming patient outcomes. The evaluation, spanning multiple databases for ocular and skin pathologies, underscores the importance of embracing these technologies to ensure the accuracy and reliability of the models. The benefits of incorporating such modules are multifaceted, addressing the challenges posed by the expanding volume and complexity of medical imaging data. By automating image classification tasks, these modules empower healthcare professionals to prioritize patient care amidst the diverse imaging modalities and datasets they encounter.

Furthermore, the deployment of machine learning algorithms significantly augments diagnostic precision and efficiency. Rapid categorization of medical images not only expedites diagnoses but also facilitates the identification of patterns, anomalies, and potential disease indicators. This, in turn, contributes to the overall reliability of medical interpretations. The establishment of an automated module sets the stage for standardized analysis, mitigating subjectivity in manual image interpretation. This standardization ensures a uniform and reproducible approach to diagnosis, fostering collaboration among healthcare professionals and promoting seamless information exchange.

As healthcare systems embrace patient-centric models, the integration of automated classification aligns seamlessly with the objective of delivering personalized and timely care. The ability to quickly analyze medical images facilitates prompt decision-making, leading to timely treatments and interventions. Our comparative analysis of web-based machine learning models, including Google Vertex AI, Google Teachable Machine, Azure Machine Learning and Salesforce Einstein Vision, aims to identify the most suitable candidate for integration into a medical information system as a classification module. Leveraging automated classification, a significant advancement in the efficiency, accuracy, and overall quality of healthcare diagnostics is anticipated, ultimately contributing to the ongoing evolution of medical practices in the era of artificial intelligence.

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