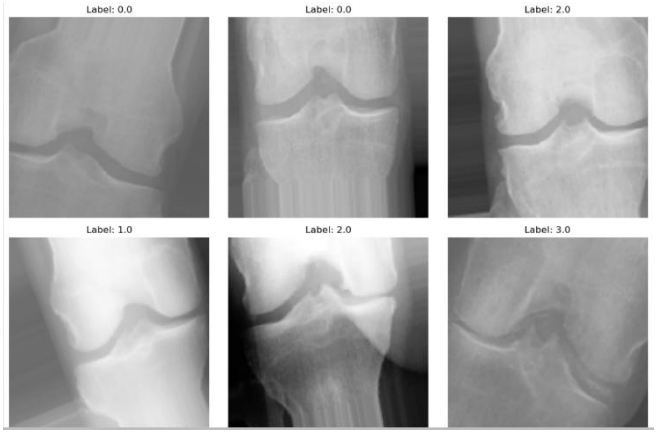
# Research Proposal of Machine Learning in Detection OF Osteoarthritis.

## Introduction




Osteoarthritis (OA) is a joint disease which can occur in any joint of the human body (mostly found in hip joints and knee joints) (mayo clinic, 2021). OA affects cartilage and surrounding structure of the entire joint including trabecular bone, femoral head, bone tissues ligament, synovial fluids, hyaluronic acid (which helps synovial fluid lubricate the joint), subchondral bone (located underneath the cartilage).

Osteoarthritis (OA) has stage I-IV stages. **Stage 0** (Pre-OA) has no clinical sign of the joint pathology but is characterized by an appearance of cellular changes. No other surface lesion is observed but MRI might detect pre-OA. Treatment involves change in lifestyle. Early stage of OA, also referred to as **Stage 1**, exhibits negligible cartilage injury and development of bone spurs but patients rarely complain of pain. It is usually diagnosed by physical examination or imaging studies, and its treatment does not involve surgery; instead, it may involve modified diet and regular exercises or change in weight. Mild OA at **Stage 2** involves more the formation of bone spur as well as slight narrowing space in joint as well as frequent pain frequently. Diagnosis is done through X-ray and the treatment as suggested includes NSAIDs, braces and exercises. Moderate osteoarthritis (OA) is categorized in **Stage 3** characterized with major cartilage loss and worsening pain during and after the exercise. It may be diagnosed using MRI or arthroscopy or through a surgical procedure; the treatments are through drugs, physical therapy and administration of injections for patients in severe pain. **Stage 4** severely limits their movement and has constant pain and stiffness coupled with very minimal or no cartilage at all. This is diagnosed using images and osteotomy or joint replacement may be needed since cure usually necessitates intervention ((Bandoim, 2023; Surmachevska and Rubio, 2023; Horváth et al., 2023)).

Osteoarthritis (OA) is a complex and disabling condition that led to $140 billion in healthcare expenses and $164 billion in lost wages in the United States in 2013 alone (Murphy et el., 2018). Additionally, with an aging global population, the prevalence of osteoarthritis (OA) is continuing to increase [5]. Artificial Intelligence (AI) and Machine Learning (ML) can help clinicians to detect OA and its pathology where ML can also help with personalized treatments. This method allows us to use multidimensional and multi-source data to understand the nature of OA (Arbeeva et al., 2023).

The complexity and diversity in both the structural and clinical aspects of **osteoarthritis (OA)** have made it challenging to develop effective treatments to slow or stop the disease's progression. Due to this challenge, the focus on AI driven technology to detect OA at its earliest stage has been a considerable topic to discuss and to explore.

## Literature Review

PubMed Research Summary: Osteoarthritis and Machine Learning (Oct 1 – Nov 3, 2024)

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The PubMed research was performed during the time period from October 1 to November 3 of 2024 using the keyword search of "Osteoarthritis" and "Machine Learning" which focused on articles from the previous twelve months. A total of 178 published articles were retrieved but we selected 43 articles based on their titles and abstracts. The review of complete texts led to selection of thirty articles for final examination. Research articles were grouped into three distinct fields: Life-style assessments enabled by ML, Image processing with ML and Genetic information examined through ML.

## A. Lifestyle Related ML Study

Widera and cooperative researchers developed a system to forecast which osteoarthritis patients would undergo fast disease worsening. The study pioneer enrollment process improves RCTs by finding individuals experiencing rapid disease progression. The authors analyzed Cohort Hip together with Cohort Knee (1002 patients) alongside Osteoarthritis Initiative (OAI) (3465 patients) while applying six various ML algorithms to clinical and X-ray data that included Total Joint Replacement (TJR) outcomes. The prediction models based on ML proved better than traditional methods which only reached 20% accuracy and delivered approximately 45% accuracy levels. More validation from external sources remains necessary for the system (widera et al., 2020).

The research team consisting of Nielsen et al. (2024) implemented XGBoost ML for the prediction of OA risk across five years by analyzing socio-demographic, lifestyle and longitudinal EHR data. The model predicted OA in 70% of future cases with an ROC-AUC score of 0.72 (95% CI: 0.71–0.73) and a 66% true-positive rate and a 67% true-negative rate. The prediction performance measured through ROC-AUC score for different joints ranged between 0.67–0.73 but knee scores reached 0.73 while hip scores hit 0.72. The SHAP values revealed age together with NSAID consumption combined with body mass index plus walking speed and vitamin D measurement as essential predictors. The patient groups generated by cluster analysis contained distinct risk factors among different patient populations.

## B. Image Related ML Study

Through their 2023 research Dorraki together with his team developed a graph theory-based network method to observe structural differences between healthy and osteoarthritis affected hip bones. The image classification process based on a CNN model established relationships between particular bone pattern abnormalities and OA disease manifestations.

Researchers from Bonakdari et al. (2022) designed a method to forecast cartilage loss detection in knees through MRI-based bone curvatures evaluation. Using gender-specific simulation data the researchers examined eight knee regions and established the medial condyle as the location where cartilage degeneration occurs most frequently. The adaptive neuro-fuzzy inference system performed the best using 10 input variables which achieved an R-value of 0.78 throughout the test and validation phases.

Zhao et al. (2024) conducted research to assess if deep learning (DL) models could identify knee osteoarthritis (KOA) severity through Kellgren-Lawrence (K-L) grading (0–4). The authors evaluated 29–30 deep learning models on 19,745 K-L0, 8221 K-L1, 11,057 K-L2, 6349 K-L3 and 2630 K-L4 X-ray images to show better performance identifying severe (K-

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L3 and K-L4) rather than milder (K-L1 and K-L2) knee grades but encountered common mistakes in distinguishing adjacent moderate grades.

Leung et al. (2020) conducted research to forecast Total Knee Replacement (TKR) risks during nine years by developing multitask DL models with transfer learning methods applying to X-ray images. The research team obtained an AUC score of 0.87 with their model which exceeded both KL grade analysis at 0.74 and the OARSI model at 0.75. The performance of the KL model indicated 91% sensitivity but its specificity measured at 58%. By using the multitask DL model operators could simultaneously achieve high accuracy in sensitivity and specificity and interpret joint space narrowing through the "zombie plot" domain. BMI data along with knee injuries together with pain scores acted as critical predictors but the inclusion of other variables resulted in reduced significance of contralateral knee data.

## C. Gene Related ML Study

Bonakdari et al. conducted research to determine if the analysis of genetic elements together with age measurements and BMI helped predict structural knee OA. The researchers evaluated 901 participants from OAI data through hybrid ML models they validated against external data from Tasmanian Older Adult Cohort Study. The study demonstrated that initial models reached 95% accuracy but external tests validated at 85% accuracy showing genetic and clinical information effectively predicts osteoarthritis development (Bonakdari H et al., 2022).

Researchers conducted a DNA methylation study to identify biomarkers for osteoarthritis progression through pattern analysis by Arbeeva L et al. (2023). Three groups consisting of 554 OAI patients and 128 Johnston County participants together with 56 additional OAI participants provided data for this study. Elastic net-regularized logistic regression successfully identified associations between methylation patterns and different categories of OA progression such as pain-only and radiographic-only and both scenarios. Analysis models that included DNA methylation data displayed superior diagnostic capabilities than clinical-only models regarding pain-related progressive disease (AUC 0.54–0.68). The continued analysis revealed thirteen CpG sites functioned as positionable OA progression indicators which displayed reliability when tested both internally among datasets and externally with additional testing methods.

WGCNA became a key methodology in Liu et al.'s (2024) research which revealed gene modules connected to traits associated with OA progression. Researchers used LASSO and Random Forest approaches in ML to discover the four biomarkers which include HSPA5, UBL4A, ATF4 and PPP1R15A. Strong diagnostic ability was confirmed by the high AUC scores obtained during model performance testing. The CIBERSORT analysis method evaluated immune cell proportions while showing relationships between the biomarkers and immune responses. The levels of biomarkers were validated by qRT-PCR to verify their significance in diagnosing OA.

# Methodology

## 1. Data Set

We obtained a publicly available osteoarthritis (OA) detection dataset from

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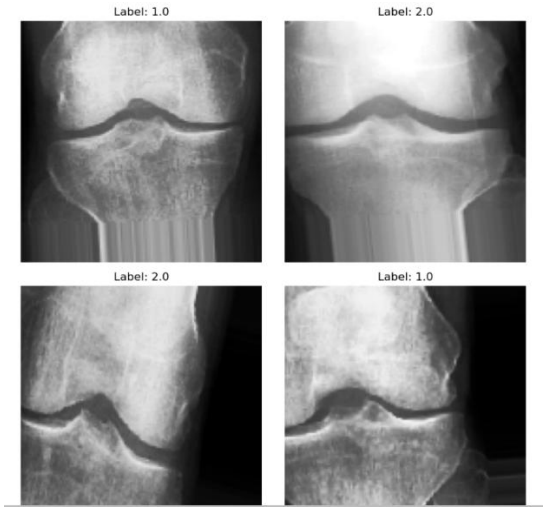
Kaggle for our project, organized into training, testing, and validation sets with KL grades 0 to 4. The dataset had significant class imbalance, which we addressed through class weighting and data augmentation. KL grades 3 and 4 were merged to improve model stability and focus on early OA detection (Hunter & Bierma-Zeinstra, 2019). However, poor image labeling and pixel quality affected the dataset's reliability. Attempts to access the OAI dataset were denied, highlighting the challenges faced by non-PhD researchers in obtaining clinically validated medical datasets (Litjens et al., 2017).

## 2. Data Analysis


The model training in our project started with a complete analysis of the available data. The dataset showed significant class imbalance consisting of 0: 2286 images while 1 contained 1046 images and 2 presented 1516 images and 3 included 930 images. A weighting system for classes was established before the model training process to reduce the impact of unbalanced classes. The calculated class weights comprised 0: 0.6318 and 1: 1.3809 and 2: 0.9528 along with 3: 1.5532 to enhance the importance of minority classes during loss evaluation. The proper management of class imbalance stands vital for medical image classification because unbalanced datasets tend to produce prediction biases that favor majority classes according to Johnson and Khoshgoftaar (2019). When balancing was absent from the model it would have overlooked significant events (grade 3) despite constantly guessing the more prevalent findings (grade 0). Class weighting proved essential during preprocessing because it enhanced model fairness across different KL disease grades.




Different preprocessing procedures were evaluated to enhance the model determination yet not all procedures yielded beneficial accuracy changes. The tried preprocessing methods included histogram equalization and Gaussian blurring together with noise cancellation techniques that produced no favorable outcomes. The histogram equalization method for contrast enhancement occasionally modified pixel values until they reached a point where important OA identification features became indistinguishable (Pizer et al., 1987). The noise cancellation method of median filtering proved suitable for regular image denoising functions yet caused the disappearance of essential fine joint structure elements that physicians need to perform KL grading. The goal of Gaussian blurring to minimize image noise along

with detail loss resulted in the model's performance deterioration while detecting different stages. The diagnosis-relevant fine tissue structures and patterns embedded in medical image matrices become compromised through any processing techniques effective on standard imagery according to Litjens et al. (2017). These methods ended up being removed from all stages of our preprocessing process.

The preprocessing method that provided best results involved data augmentation through ImageDataGenerator from TensorFlow. Data augmentation performed effectively through its ability to augment the dataset and create additional data points that minimized model overfitting while developing better robustness. The data augmentation scheme using TensorFlow's ImageDataGenerator included pixel value rescaling to 1./255 and image rotation up to 30 degrees and horizontal-vertical shifting by 20% and brightness range of 0.8 to 1.2 shear transformation along with 20% zooming and random horizontal flipping and pixel "nearest" interpolation for missing pixel filling. These simulated spatial changes retain original anatomical structures to boost generalization abilities (Shorten and Khoshgoftaar, 2019). When augmentation techniques were applied to the model it proved beneficial to validation performance particularly among minority classes.

The implementation of these techniques used TensorFlow as the machine learning framework developed by Google (Abadi et al., 2016). The multiple features of TensorFlow help users build models and preprocess data which makes it excellent for performing deep learning duties with big image datasets. Through its ImageDataGenerator class TensorFlow enables effortless real-time data augmentation that distributes augmented batches to the model during training without taking up excessive system memory. The flexibility together with scalability and broad support network of TensorFlow users made the platform our primary selection for the project. The combination of advanced preprocessing techniques with TensorFlow data pipelines enabled us to build a model that better understood the fine details needed for early osteoarthritis diagnosis.

## 3. Model Implementation

### a. CNN

We developed a tailored Convolutional Neural Network (CNN) through TensorFlow and Keras which performed classification of osteoarthritis (OA) stages through KL grading. Our CNN model contained four blocks which increased their filter dimensions starting from 32 and ending with 256. The CNN had four convolutional blocks which included 3x3 kernel size and ReLU activation and subsequent batch normalization and max-pooling layers that stabilized learning while reducing spatial volume. The model reached accelerated convergence along with improved overall stability because of batch normalization (Ioffe and Szegedy, 2015). A dropout layer steadied overfitting by setting the rate to 0.3 while dense layers with 256 ReLU-activated neurons combined with flattening and dropout in the network design. The last layer added a dense output component that used softmax

activation to generate predictions from five KL grades starting from zero and ending at four. The Adam optimizer with learning rate 0.0001 was used to compile the model which ensured smoother convergence according to Kingma and Ba (2015). The chosen loss function was sparse categorical cross-entropy which works properly with integer target distributions. We used class weights in training to maintain the proper emphasis on minority classes which normally receive less attention. The model used Early stopping along with ReduceLROnPlateau callbacks to track validation loss for overfitting prevention and automatic learning rate adaptation. The training process used data from ImageDataGenerator while operating for as many as 30 epochs. The deep learning model benefited from the efficient modular system provided by TensorFlow and Keras (Abadi et al., 2016) which led to quality outcomes despite data-related challenges (Abadi et al, 2016).

### b. VIT

The second model selection for osteoarthritis (OA) stage classification involved the Vision Transformer (ViT). The research utilized the PyTorch framework to implement ViT because of its accepted features including flexibility alongside dynamic computation graphs and strong GPU acceleration capabilities (Paszke et al., 2019). Our experiment applied the Google pretrained ViT-Base-Patch16-224 model from the ImageNet-1K dataset that consists of 1,000 classes (Dosovitskiy et al., 2021). Transfer learning became feasible since the model's initial feature collection provided a streamlined adaptation to our unique medical imaging scenario. The Vision Transformer represents a transformation from the conventional architecture of convolutional neural networks (CNNs). The design of ViT embeds each image into fixed-size patches (16x16 pixels) before flattening them and applying linear embedding. The standard Transformer encoder processes the linearly embedded patch sequences as ordinal elements even though it was originally designed for textual data (Vaswani et al., 2017). The design enables ViT to establish long-distance connections between various image sections since deployment from the start while offering specific advantages for medical images when diagnosing stages of disease. We changed ViT's last layer for our dataset class count before training with CrossEntropyLoss and AdamW optimization. The training process took place on a GPU device to optimize execution speed. ViT succeeded in medical imaging tasks because its exceptional ability to analyze global and fine-grained image features. The saved trained model gave us the capability to use it for future tests which led to potential clinical usage. Our project benefited greatly from adding ViT as a result of all the pretrained architecture tests we performed.

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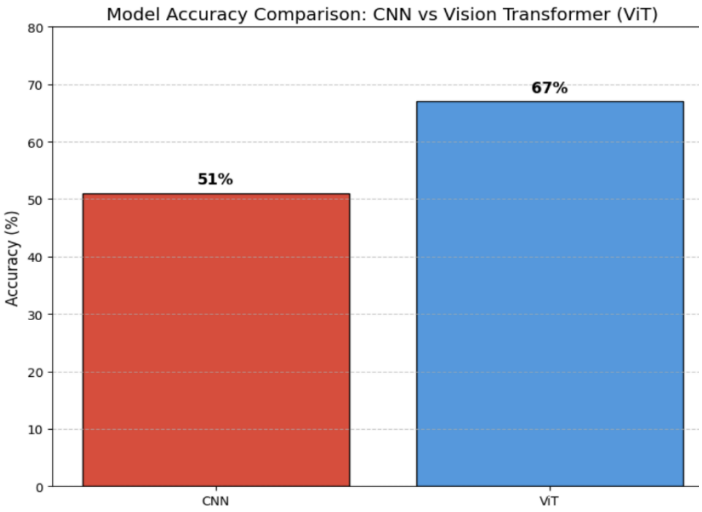
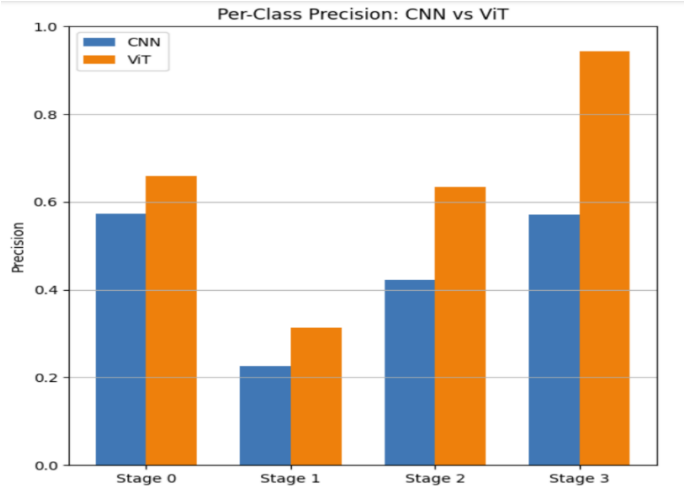
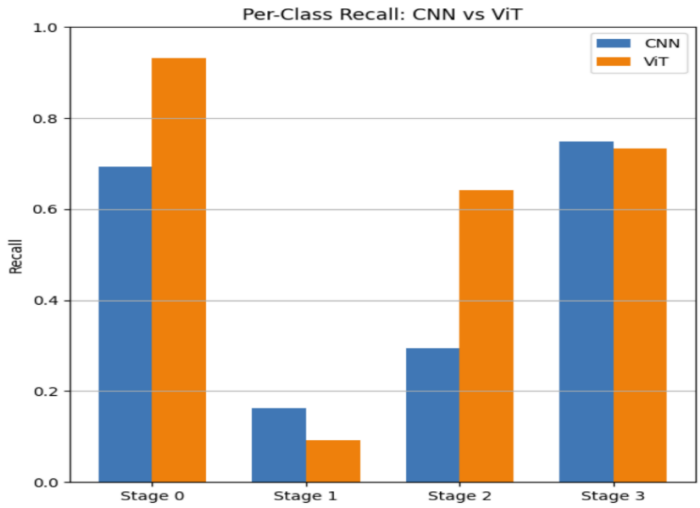
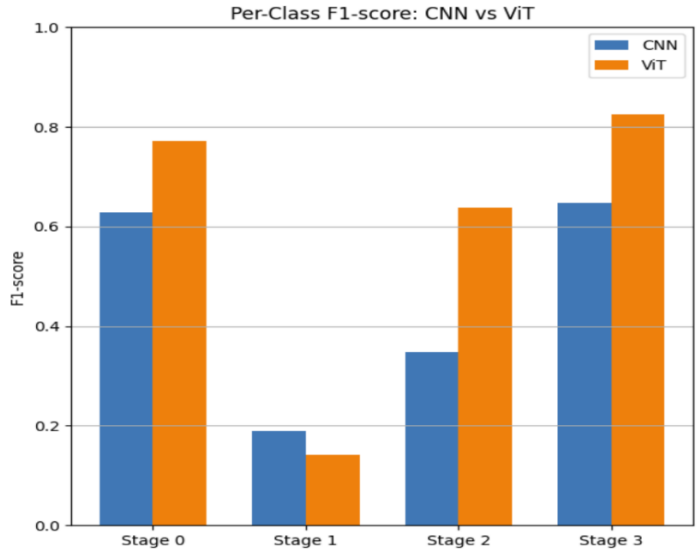
## Results




Our project evaluated the ViT and CNN models for detecting osteoarthritis (OA) by using KL grading methods. The Vision Transformer reached 67.09% test accuracy as it surpassed the CNN technique which produced a total accuracy of 51%. The ViT model reached 93.27% class 0 accuracy together with 9.12% class 1 performance and 64.21% class 2 accuracy and reached 73.36% accuracy for class 3. The CNN model delivered test accuracy results for class 0 at 67.1% while achieving 18.2% for class 1 and 28.9% for class 2, and finally 71.5% accuracy for class 3. Both ViT and CNN exhibited unsatisfactory accuracy rates for diagnosing early mild OA (class 1) which amounted to 9.12% and 18.2% respectively. The analysis confirmed that both labeling quality and pixel clarity of early stages of OA affected the testing outcome due to data collection defects. Certain images from class 1 and some instances of inadequate resolution together with contrast issues prevented proper identification of subtle structural modifications which are essential for accurate classification. The substandard data quality presented a major obstacle for advanced architectures to accurately determine early-stage OA. Video-based Image Transformer achieved better accuracy distribution among different classes while Convolutional Neural Networks experienced greater difficulties in maintaining reliable accuracy levels particularly for intermediate categories of class 2.



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The evaluation metrics included precision, recall alongside F1-score for determining the performance of both models. The ViT model delivered outstanding performance with improved precision and recall effectiveness on classes 2 and 3. This indicates the model's ability to both identify correct diagnoses and cut down on wrong negative results. Such detection accuracy is fundamental in medical applications because early-stage OA diagnosis can help initiate necessary treatment procedures on time. Through its self-attention mechanism the Transformer component enables ViT to identify and prioritize image regions that matter which results in better healthcare diagnostic performance when compared to CNNs which tend to lose detailed information during pooling operations (Touvron et al., 2021). The generalization ability of ViT during fine-tuning on ImageNet-1K pretrained weights proved essential for achieving high performance (Dosovitskiy et al., 2021). The powerful nature of CNNs comes with the need for substantial annotated data because equivalent generalized results require extensive datasets. The smaller annotated medical datasets would benefit from ViT's transfer learning capability which delivered improved outcomes in our research. The research findings illustrate that the Vision Transformer outperformed the CNN model in detecting OA based on KL grading because it produced superior accuracy and precision and recall and F1 scores across most classes. The medical imaging application shows the Vision Transformer excels due to its global relationship capturing ability together with powerful transfer learning features and attention-based features.

## Discussion

The project utilized an osteoarthritis detection dataset from Kaggle which contained training and validation and testing sections that presented KL grades ranging from 0 to 4. And because the dataset contained severe class unbalance we executed data augmentation and class weighting to overcome this deficiency. The combination of KL grades 3 and 4 served our purpose because early-stage diagnosis holds critical value in clinical practice (Hunter & Bierma-Zeinstra, 2019). The ViT vision transformer model was chosen to perform classification duties following image preprocessing. The exploited advantages of ViT failed to overcome the negative influence of label errors and pixel degradation within the dataset which led to decreased detection accuracy in early-stage osteoarthritis cases. Access to the Osteoarthritis Initiative (OAI) dataset for high-quality radiographic images proved impossible because researchers independently face difficulties when obtaining clinically validated data according to Litjens et al. (2017). Regardless of the complexity of the model design data quality maintains its vital role in operation

maintained superior performance than the CNN model in every class examination. The

## Conclusion

The Vision Transformer (ViT) showed better performance than the CNN model in OA detection yet the final results depended strongly on the quality of available data. Insufficient labeling practices together with image degradation mainly affecting early-stage OA restricted the complete potential of high-end architecture ViT. The future implementation of active learning features will boost model reliability because it lets the system ask experts to label ambiguous samples thus creating training data that grows more effective. The deployment of reinforcement learning strategies will optimize decision processes and improve trustworthiness standards for clinical acceptance. Medical decisions must rely on validated high-quality data because poor data quality cannot be resolved by the best models

available. Building reliable physician-oriented AI tools requires strong data collection combined with constant model evolution and skilled learning strategies in addition to the selection of proper models.

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