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Article

MRI-Based prototype for early detection of muscular knee injuries with U-Net

Prototipo basado en resonancia magnética para la detección precoz de lesiones musculares de rodilla con U-Net

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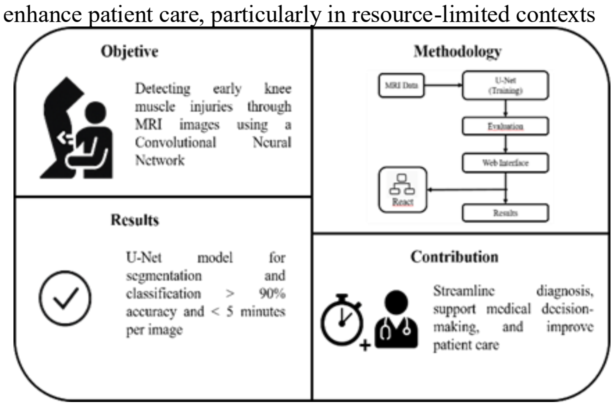
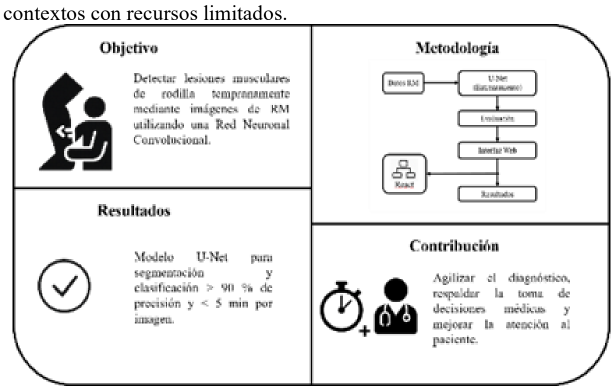
Abstract

This study presents the development and initial validation of an Artificial Intelligence [AI] based prototype for the early detection of knee muscle injuries using Magnetic Resonance Imaging [MRI]. The system leverages a U-Net architecture for lesion segmentation and classification, achieving performance above 90% in preliminary tests while reducing analysis time to less than five minutes per case. The development methodology included data preprocessing, model training and performance evaluation, as well as the implementation of a web interface [React for the frontend and Python for the backend]. The solution is designed for deployment in clinical settings, aiming to streamline diagnosis, support medical decision-making, and enhance patient care, particularly in resource-limited contexts



Resumen

Este estudio describe el desarrollo y validación inicial de un prototipo de apoyo al diagnóstico basado en Inteligencia Artificial[IA] para la detección temprana de lesiones musculares de la rodilla mediante imágenes de Resonancia Magnética [RM]. El sistema emplea una arquitectura U-Net para la segmentación y la clasificación de lesiones; en las pruebas realizadas alcanzó un desempeño superior al 90 %, lo que reduce el tiempo de análisis a menos de cinco minutos por estudio. La metodología de desarrollo comprendió el preprocesamiento de datos, el entrenamiento del modelo y la evaluación del desempeño, así como el desarrollo de una interfaz web [React para el frontend y Python para el backend]. La solución está concebida para su despliegue en entornos clínicos, con el objetivo de agilizar el diagnóstico, respaldar la toma de decisiones médicas y mejorar la atención al paciente, especialmente en contextos con recursos limitados.



Artificial Intelligence, Convolutional Neural Network, Magnetic Resonance Imaging

Inteligencia Artificial, Red Neuronal Convolucional, Resonancia Magnética

Area: Development of strategic leading-edge technologies and open innovation for social transformation

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Introduction

According to recent estimates on the global burden of disease, more than 1.7 billion people suffer from musculoskeletal disorders. Although they affect individuals of all ages, their prevalence varies depending on the diagnosis and stage of life. High-income countries concentrate the largest number of cases [441 million], followed by the Western Pacific and Southeast Asia regions [427 and 369 million, respectively]. These disorders constitute the leading cause of Years Lived with Disability [YLD], accounting for approximately 17% of the global total, which is equivalent to about 149 million YLDs [World Health Organization, 2022].

In the Mexican context, musculoskeletal disorders [MSDs] represent one of the main causes of disability, and their burden has increased significantly in recent decades. According to estimates from the Global Burden of Disease 2021, between 1990 and 2021, the YLDs attributable to MSDs increased by 57.3%, rising from 1,458.4 to 2,293.7 per 100,000 inhabitants. Low back pain ranked as the most disabling condition, with 840.6 YLDs per 100,000 inhabitants, while osteoarthritis showed the greatest proportional increase [Clark et al., 2024].

Additionally, musculoskeletal injuries particularly those affecting the knee joint represent a significant problem in both clinical and sports settings. These injuries can considerably limit mobility, cause chronic pain, and reduce patients' quality of life if they are not diagnosed and treated in a timely manner. Diagnosis often implies high costs, prolonged evaluation times, and variability in outcomes depending on the clinician's experience [Padilla-Rojas et al., 2024; López et al., 2023]. According to the World Health Organization [WHO], access to advanced imaging diagnostic technologies is concentrated in countries and centers with high resource availability, creating a significant gap in educational institutions and secondary-level hospitals [World Health Organization, 2022]. Similarly, the Pan American Health Organization [PAHO] reports that Latin America faces considerable limitations in the availability of automated technologies and specialized diagnostic software, which delays early clinical assessment and increases health system costs [Health Technology Assessment, 2025].

In Mexico, recent studies indicate that timely diagnosis of these conditions is hindered by the lack of accessible technological tools, particularly in public hospitals and training environments, where interpretation depends solely on the clinical judgment of specialists [Clark et al., 2024].

Given this context, the development of an intelligent software prototype is proposed for the early diagnosis of muscular knee injuries by means of automated analysis of magnetic resonance imaging supported by deep learning techniques. The implementation of Convolutional Neural Networks[CNNs] using a U-Net architecture enabled high diagnostic precision and a reduction in required evaluation time.

This article is structured into five sections. First, the Theoretical Framework describes AI and CNNs as key tools in medical diagnosis, highlighting architectures such as U-Net, ResNet-18, and MobileNetV3-Small for their effectiveness in biomedical imaging. The State of the Art presents recent applications of AI across various medical specialties, including studies on knee injury diagnosis using magnetic resonance imaging. The Methodology covers data acquisition and preprocessing, CNNs model training, and the implementation of a web prototype using React and Flask. The Results show that U-Net achieved the highest accuracy and segmentation performance compared to ResNet-18 and MobileNetV3-Small, confirming its suitability for clinical environments. Finally, the Conclusions emphasize that the system contributes to faster and more accurate diagnoses, although the need to expand the dataset is recognized, along with future improvements aimed at extending the prototype to other musculoskeletal injuries.

2. Theoretical Framework

AI a branch of computer science focused on logic and learning, enables the design of systems capable of simulating human cognitive processes such as learning, reasoning, and self-correction [Ruibal-Tavares et al., 2023]. Driven by advances in infrastructure and computing capacity, including in low- and middle-income countries,

AI has gained momentum and has emerged as a key tool to address global health challenges [Schwalbe & Wahl, 2020].

This scenario opens opportunities for diagnostic support through automated analysis of clinical data and medical imaging, contributing to more timely decision-making and improved resource allocation.

In the healthcare sector, AI-based approaches have become consolidated as crucial tools, providing innovative solutions in diagnosis, prognosis, and treatment. In particular, deep learning and CNNs]have demonstrated high effectiveness in the interpretation of medical images with high precision, even in resource-limited settings, thus promoting equity in healthcare access. These networks, inspired by the connectivity of the human visual cortex, have been widely used in medical image processing and clinical diagnostic support [Craig & Awati, 2024].

The structure of CNNs consists of:

- Convolutional layers, which detect specific features through filters that generate activation maps.
- Pooling layers, which reduce dimensionality and preserve key information.
- Fully connected layers, responsible for the final classification by integrating all extracted features.

One of the milestones in the evolution of these networks was AlexNet, developed by Krizhevsky and Hinton, which significantly outperformed other techniques in image recognition competitions and marked a turning point in the field of deep learning [Badillo et al., 2021].

In this work, three CNNs architectures widely used in biomedical domains were considered: U-Net, ResNet-18, and MobileNetV3-Small.

U-Net

U-Net is a biomedical segmentation architecture based on an encoder–decoder scheme with skip connections that preserve spatial information, making it particularly effective in environments with limited datasets. Recent reviews have confirmed its flexibility and high performance across multiple medical imaging modalities such as magnetic resonance imaging, computed tomography, and microscopy, even when the number of annotated samples is limited [Isensee et al., 2020].

A recent taxonomy has classified U-Net variants according to image modality and clinical application, including their use in brain tumor segmentation, lung cancer, Alzheimer's diagnosis, breast cancer, and COVID-19 detection [Ali et al., 2021]. Among proposed improvements, Sharp U-Net stands out, incorporating depthwise convolutions and sharpening filters to effectively combine extracted features in the encoding and decoding stages, achieving more precise segmentations without significantly increasing the number of parameters [Rahman et al., 2021].

ResNet-18

ResNet-18 is a deep residual network that uses shortcut [residual] blocks to mitigate the vanishing gradient problem and enable stable training in deeper architectures. Recent medical applications have demonstrated strong performance, such as in the classification of lesions in multiparametric prostate MRI, including those categorized as intermediate [PI-RADS 3, indeterminate probability of clinically significant cancer], achieving high precision and competitive area-under-curve metrics in multi-category classification scenarios [Wang et al., 2024].

MobileNetV3

MobileNetV3 is an architecture optimized for devices with limited computational resources, based on depthwise separable convolutions and squeeze-and-excitation blocks, enabling reduced training time and memory usage. Its combined version with U-Net, called MobileUNetV3, has shown outstanding results in spinal cord gray matter segmentation, demonstrating that high precision can be maintained with a lightweight architecture [Zhou et al., 2022]. Additionally, MobileNetV3 has been used as an efficient classifier in histopathological breast cancer imaging, achieving high accuracy in malignant pattern identification with reduced computational cost [Kumar et al., 2024].

3. State of the Art

Several recent studies highlight the application of AI in different medical specialties, as shown in Table 1, extracted from the review by Ruibal-Tavares et al. [2023]. The techniques used range from Deep Neural Networks [ANN], machine learning, to specialized CNNs, depending on the application field and the type of clinical data analyzed.

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Box 1

Table 1

Relevant applications of AI in medicine.

Medical Specialty	Tecnologías de IA	Relevant Applications
Radiology	Deep ANN	Detection of pulmonary nodules, coronary calcium scoring in CT
Cardiology	ANN, XGBoost	ECG-based diagnosis, hypertension prediction
Ophthalmology	CNN	Detection of retinal neovascularization and macular degeneration
Dermatology	Deep learning	Diagnosis of melanoma and basal cell carcinoma using dermatoscopic images
Neurology	Machine learning	Prediction of ischemic stroke and epilepsy risk
Pathology	Deep learning, machine learning	Classification of neoplasms by DNA methylation, hepatic steatosis
Genetics	Deep ANN	Analysis of pathogenic genetic variants
Gastroenterology	CNN, machine learning, 5G recognition	Diagnosis of celiac disease using endoscopic imaging

Source: Ruibal-Tavares et al., 2023

Qiu et al. [2021] developed a model called CNNss, which combines two convolutional networks to identify meniscal injuries. Their results show that the use of magnetic resonance imaging significantly outperforms the diagnostic accuracy of traditional computed tomography.

Similarly, Trejo-Chávez et al. [2022] proposed a methodology that includes data augmentation, robust image preprocessing [such as rotation, noise, and brightness adjustments], and training of CNNs under different configurations. This approach strengthens the model's adaptability to real-world conditions.

Finally, Cueva et al. [2022] presented a computer-assisted diagnostic system based on Siamese networks and ResNet-34 to simultaneously evaluate X-ray images of both knees, allowing the classification of osteoarthritis severity with high accuracy.

These studies demonstrate the applicability of AI, particularly CNNs, in the automated diagnosis of joint and musculoskeletal injuries, establishing a solid foundation for their integration into clinical systems.

4. Methodology

The methodology was structured into two main components:

- Development of the AI model for the segmentation and classification of muscular knee injuries.
- Development of the web prototype and clinical database.

The development of this model comprises four stages:

Box 2

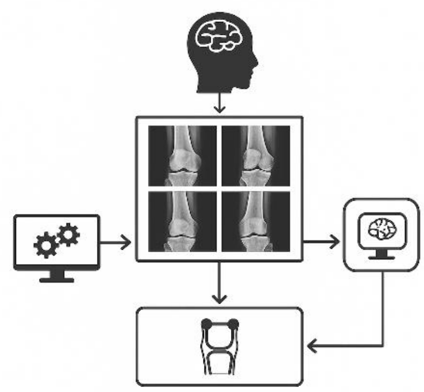

Figure 1

Development diagram of the AI models

Source: Author's elaboration

The first stage is the acquisition of medical images: MRI]or radiographic images are collected to form the database that will feed the AI model. These images may be obtained from clinics, hospitals, or specialized repositories.

For this research, the MRNet-v1.0 dataset was used, composed of a total of 1,370 MRI studies divided into three modalities: T1 sequence, T2 sequence, and proton-density images. These images were carefully selected and annotated by expert radiologists, ensuring quality and clinical relevance. Each image is associated with labels indicating the presence or absence of lesions, enabling classification and segmentation model training.

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The second stage is preprocessing, through which the images undergo normalization, segmentation, noise reduction, and data augmentation, ensuring they are in optimal condition for training.

Preprocessing included:

- Pixel intensity normalization.
- Resizing and padding to 256 × 256 pixels.
- Data augmentation through rotations, cropping, and brightness adjustments.
- Organization by anatomical view: coronal, sagittal, and axial.

In the third stage, the AI model is trained. A Convolutional Neural Network or specialized architecture such as U-Net is applied to learn patterns and detect possible lesions in the knee.

- Training and Evaluation Environment
- Platforms: Google Colab [GPU Tesla T4] and Intel i7 CPU for local tests.
- Data split: 70% training, 15% validation, 15% testing.

Training Functions and Optimization:

- U-Net → BCEWithLogitsLoss, AdamW optimizer, mixed precision using GradScaler[] for GPU acceleration.
- ResNet-18 and MobileNetV3 → Configured in environments optimized for binary classification.
- Metrics: Accuracy, IoU, Dice Score, training time.

The models were trained for a maximum of 20 epochs, using validation at each iteration. An early stopping strategy with a patience of 10 epochs was implemented, such that training would stop automatically if no improvement was observed in the validation metric [Dice Score].

This approach prevented overfitting and optimized computational resource usage, ensuring that the model reached a stable performance without unnecessarily extending the training process.

Additionally, a decision threshold of 0.5 was defined for classifying each pixel as lesion or healthy tissue. Values equal to or greater than the threshold were classified as lesion, while those below were classified as healthy.

This criterion enabled the calculation of complementary metrics, including the number of False Positives [FP] and False Negatives [FN], as well as the confusion matrix to evaluate prediction quality.

The final stage corresponds to results generation: The system produces a visual or diagnostic output, such as lesion detection or segmentation in the knee, which can support medical decision-making.

Development of the Web Prototype and Clinical Database

Development Methodology

An agile approach based on the Kanban methodology was adopted. Short iterations and periodic reviews by clinical personnel allowed functionalities to be adjusted according to real project needs. A project schedule was defined and roles were assigned, supported by the Jira project management tool.

Frontend

The interface was developed in React.js with responsive design, enabling:

- Uploading MRI images.
- Display of segmentation results generated by the model.
- Registration of clinical observations xzsaq linked to each patient.

Backend

The backend was implemented in Flask [Python] with the following functionalities:

- Execution of the U-Net segmentation model.
- Generation and processing of segmentation masks.
- Communication with the frontend using Flask-CORS.
- Integration with PyTorch, OpenCV, and NumPy.

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Box 3

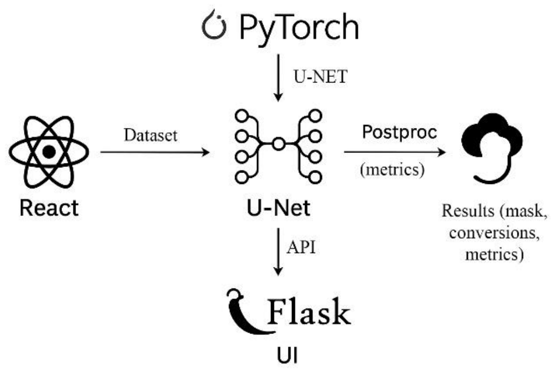

Figure 2
System architecture diagram

Source: Author's elaboration

Purpose

To develop an MRI-based software prototype for the early detection of muscular knee injuries, facilitating identification and diagnostic support through automated image analysis.

Scope

The project aims to provide a tool that enables early diagnosis of muscular knee injuries using MRI image processing and deep learning, adaptable to clinical and academic environments.

5. Results

Development of the AI Model

The results obtained during the experimental phase allow for the evaluation of the performance of the three CNNs architectures: U-Net, ResNet-18, and MobileNetV3-Small, trained for the detection of muscular knee injuries using magnetic resonance imaging, as shown in Table 2.

Box 4

Table 2
Training results of the evaluated models.

Model	Accuracy	Training Time [Colab]	Training Time [PC]
U-Net	91%	1 hour 36 minutes	30 minutes
ResNet-18	89%	14 minutes	14 minutes
MobileNetV3	88%	12 minutes	10 minutes

Source: Author's elaboration

The U-Net model demonstrated the best performance in terms of accuracy and segmentation quality, proving particularly useful in simulated clinical environments where diagnostic precision is prioritized. Its encoder-decoder structure with skip connections allows for more precise segmentation of muscular structures.

Box 5

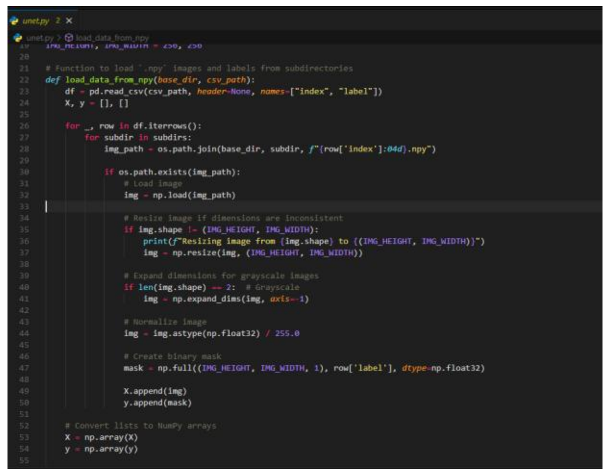

Figure 3
Model development

Source: Author's elaboration

Desarrollo e Implementación del prototipo Web

Frontend: A responsive interface developed in React.js enables clinical personnel to:

- Upload MRI scans.
- Visualize segmentation outputs generated by the model.
- Record clinical observations linked to each patient.

Box 6

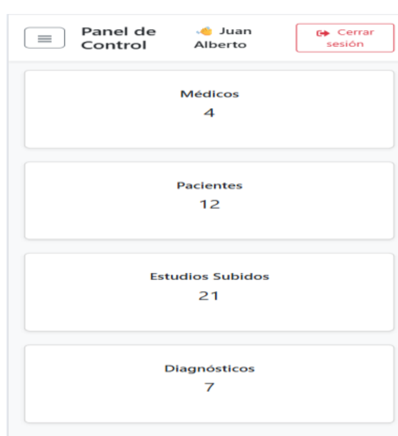

Figure 4
Prototype dashboard

Source: Author's elaboration

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Box 7

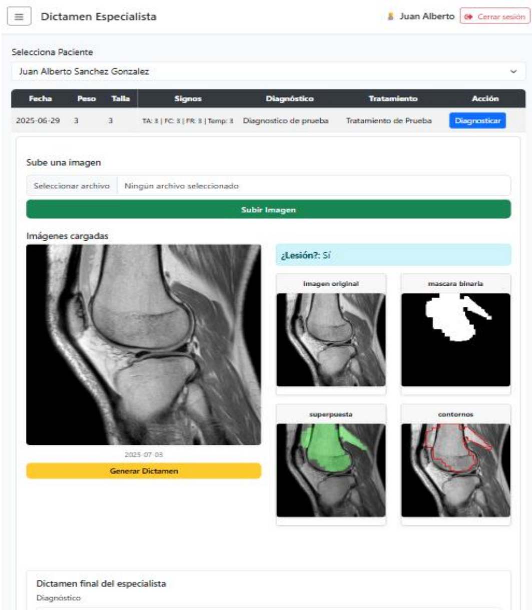

Figure 5
Lesion prediction output

Source: Author's elaboration

Backend: Implemented in Flask [Python], responsible for:

- Executing the U-Net model.
- Generating segmentation masks.
- Returning predictions to the user interface.

Prototype Performance Evaluation

The web prototype with the U-Net model was evaluated on a set of 20 knee MRI studies uploaded directly through the interface. The results are summarized in Table 3.

Box 8

Tabla 3
Prototype performance on 20 MRI studies.

Metric	Mean [±SD]	95% CI	Minimum	Maximum
Accuracy	91.0 % ± 2.1	[89.7 – 91.9]	87.2 %	94.1 %
Dice Score	0.87 ± 0.03	[0.85 – 0.89]	0.83	0.91
IoU	0.85 ± 0.04	[0.83 – 0.87]	0.80	0.90
Avg. time per study	4.6 ± 0.5	[4.4 – 4.9]	3.9	5.4

Source: Author's elaboration.

Interpretation of results:

- The system maintained an average accuracy of 91.0%, confirming consistent predictions in a simulated clinical environment.

- The Dice Score of 0.87 and IoU of 0.85 indicate a high level of agreement between automatic segmentations and expert references.

- The average analysis time per study was approximately 4.6 minutes, confirming the system's efficiency for real clinical workflows.

Analysis of False Positives, False Negatives, and Decision Threshold

In addition to the global metrics reported in Table 4, a detailed analysis was conducted on the 20 magnetic resonance imaging studies evaluated with the web prototype. The U-Net model assigns each pixel a probability value between 0 and 1 of corresponding to a lesion, establishing a decision threshold of 0.5.

Values equal to or greater than the threshold were classified as lesions, while values below the threshold were considered healthy tissue.

Using this criterion, the following results were obtained: 15 True Positives [TP], 2 True Negatives [TN], 1 False Positive [FP], and 2 False Negatives [FN]. Table 4 shows the distribution of the cases, while Figure 11 presents the corresponding confusion matrix.

Box 9

Table 4
Classification results across 20 evaluated studies.

Study	Actual Lesion	AI Prediction	Result
1–15	Yes	Yes	TP
16–17	Yes	No	FN
18–19	No	No	TN
20	No	Yes	FP

Source: Author's elaboration

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Box 10
Table 5
Confusion matrix for the 20 evaluated studies.

Study	Predicted Lesion	Predicted Healthy
Actual Lesion	TP = 15	FN = 2
Actual Healthy	FP = 1	TN = 2

Source: Author's elaboration.

Based on these values, the following additional metrics were calculated: a precision of 85%, a sensitivity of 88.2%, a specificity of 66.7%, a Dice Score of 0.87, and an average IoU of 0.85, results that are consistent with those obtained in the experimental phase.

Regarding the decision threshold, it was observed that a value of 0.5 achieves a balance between sensitivity and specificity. A higher threshold [0.7] reduces false positives but increases false negatives, while a lower threshold [0.3] increases sensitivity at the expense of more false positives.

Therefore, the threshold of 0.5 is considered the most suitable for initial clinical scenarios, as it maintains an appropriate balance between lesion detection and the reduction of classification errors.

6. Conclusions

The findings of this research demonstrate the technical and clinical feasibility of implementing artificial intelligence–based tools for the early diagnosis of muscular knee injuries.

The U-Net model achieved an accuracy greater than 90%, proving to be the most robust architecture under simulated clinical conditions. In addition, the analysis time was significantly reduced, contributing to faster and more timely diagnostic support.

The prototype offers an economical, accessible, and adaptable solution for institutions with limited resources, such as public hospitals or university clinics.

The combination of an intuitive web interface, trained AI models, and a structured database makes this tool a complete and functional system. Consequently, the system has high scalability potential, allowing it to be adapted to other types of musculoskeletal injuries.

Future work and improvement opportunities

- Expand the database with locally acquired clinical images to improve the model's generalization capacity.
- Integrate additional models to differentiate degrees of lesion severity.
- Implement and evaluate the prototype in the Clinical Training Center at the Universidad Tecnológica de Xicotepec de Juárez.

Declarations

SECIHTI Contribution Area

This project contributes to the axis Development of strategic cutting-edge technologies and open innovation for social transformation, by proposing an artificial intelligence–based system for the early detection of muscular knee injuries through magnetic resonance imaging, strengthening diagnostic capacity and medical care in institutions with limited resources.

Conflict of interest

The authors declare that they have no conflict of interest.

They have no known competing financial interests or personal relationships that could have influenced the results, interpretation, or presentation of this article.

Author contribution

Sánchez-González, Juan Alberto: Methodological design, development of the U-Net model, training and validation, interpretation of results, manuscript writing, and development of the web prototype.

Hernández-Reyes, José Manuel: Results analysis, model validation, technical support in implementation, and final manuscript review.

Escorza-Sánchez, Yolanda Marysol: Academic supervision, methodological guidance, and final manuscript review.

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Abbreviations

AI	Artificial Intelligence
ANN	Artificial Neural Network
BCE	Binary Cross-Entropy
CI	Confidence Interval
CNN	Convolutional Neural Network
CT	Computed Tomography
Dice	Dice Similarity Coefficient
ECG	Electrocardiogram
FN	False Negative
FP	False Positive
IoU	Intersection over Union
MRI	Magnetic Resonance Imaging
MSD	Musculoskeletal Disorder
PAHO	Pan American Health Organization
ReLU	Rectified Linear Unit
SD	Standard Deviation
TN	True Negative
TP	True Positive
WHO	World Health Organization
YLD	Years Lived with Disability

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Antecedents

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