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Prediction of Fracture Union in Long Bones Using AI Models

The predictive capability for estimating healing time in long-bone fractures is vital for improving patient outcomes and preventing of complications in orthopedics. Delays or non-union fractures if left untreated may result in sustained disability, increased medical expenses and dysfunction. The current prediction techniques are primarily based on clinical examination, X-ray interpretation and bone-turnover blood tests, which are subjective and often inaccurate. Artificial intelligence (AI) and machine learning (ML) are promising solutions to current developments. The AI models include supervised learning algorithms, neural networks and ensemble approaches that analyze multi-dimensional and complex data that comprise patient demographics, fracture characteristics, surgical history, imaging and lab findings. The AI-based models are superior in prediction compared to traditional methods because they are able to identify subtle trends among these variables. This review sums up the recent findings on AI application to the healing of long bone fractures, such as important algorithms, data sources and clinical variables to be included in the model construction. It additionally provides discussion of how the imaging modalities (plain radiographs, CT, MRI) can be integrated with AI to increase the accuracy of the diagnosis, it also mentions such challenges as the quality of data, the explainability of models and their implementation in clinical practice. Lastly, the review shows that future AI-based decision support systems can personalize treatment, enhance clinical decision-making, and eventually improve the healing process.

1.1. Introduction

Long bone fractures, including those of the femur, tibia, humerus and forearm bones, are a significant clinical problem due to their frequency, severe complications and healthcare resource requirements (Jha et al. 2025). These injuries are caused by high energy impact such as car collisions or

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height falls and low energy impact among the elderly who have weak bones. Early fracture healing is an essential step towards restoring functional status, preventing complications and reducing the social costs of prolonged rehabilitation.

The process of healing fractures is dynamic, involving inflammation, formation of a callus, ossification and remodeling. Success is determined by a vast number of factors related to patients including age, sex, comorbidities (e.g. diabetes or osteoporosis) and other lifestyle habits (e.g. smoking and nutrition) (Donié et al. 2024). The location, pattern, severity of fractures and nature of treatment (surgery or conservative care) are also factors that have a significant positive effect on outcomes. Delayed or non-union results in chronic pain, chronic immobility, loss of functional ability and possibly another surgery.

Conventional fracture healing monitoring incorporates clinical evaluation, image and laboratory findings. Skilled clinicians frequently consider pain relief, limb function restoration and weight-bearing capacity as signs of healing, however, these are subjective and cannot be related to the underlying biology (Razavi et al. 2025). Serial X-rays are by far the most commonly used method to evaluate callus formation and cortical continuity, but they are subject to interpretation bias, and the initial indicators of healing are delicate. Advanced imaging modalities, such as CT and MRI, provide greater detail, particularly in complicated or joint fractures but are not routinely used because of cost, radiation exposure, and limited availability.

Predictors of healing have also been examined through measuring blood levels of bone turnover markers, such as serum alkaline phosphatase, osteocalcin and C-terminal telopeptide (Morgan et al. 2024). Even though these biomarkers are objective, they have a low rate of clinical utility because they vary among individuals and there are no standardized cut-offs. Due to this fact, the traditional methods are often inadequate for early and precise prediction of fracture union, particularly in high-risk or complex cases.

ML and AI have become potentially valuable technologies that can eliminate these constraints (Jha et al. 2025). AI systems have the ability to break down multi-dimensional data that incorporates patient demographics, fracture features, radiographies, surgical and laboratory findings to come up with predictive models of union. Supervised learning algorithms including random forests and support vector machines are also capable of determining important predictors of delayed or non-union, whereas deep learning models, especially convolutional neural network models, are able to automatically learn features based on imaging data, thereby enhancing the prediction of delayed or non-union.

The current literature proves that AI-based models have been capable of delivering personalized prognoses, aiding clinical decision-making and streamlining patient care (Misir 2025). Using the combination of sources of data, AI algorithms can prioritize patients based on their level of risk, foster early interventions and even decrease the risk of repeated imaging. Although effectively showing good results, issues of data heterogeneity, small sample sizes, model explainability and its use in standard clinical practice continue to hamper large-scale adoption.

The main purpose of this chapter is to extensively review AI applications in predicting fracture union in long bones. It covers the nature of AI models used, predictive variables and data sources, integration of imaging modalities with AI analysis, predicted model performance and lack of guidance on the main challenges and the future of AI implementation in clinical use. It is hoped that this review will provide orthopedists, researchers and AI developers with a clear vision of the advantages and limitations of AI-based fracture union prediction and contribute to positive patient outcomes and tailored fracture treatment.

1.2. Types of AI models for fracture union prediction

Models of fracture union prediction are becoming increasingly dependent on AI. They are able to analyze intricate data and identify patterns that can easily escape clinicians.

There are four broad categories of AI models, which comprise supervised and deep, unsupervised, and hybrid or ensemble models (Elkohail et al. 2025). All types have strengths which are dependent on data and clinical circumstance.

The most common supervised learning models in the case of fracture union prediction are supervised learning models. They are trained using known datasets in which outcome; union or non-union, is known. Random forest, support vector machine, gradient boosting and logistic regression are some of the models that have been effective in predicting healing. As an example, the random forest manages various data and identifies the most significant predictors of fracture such as the type of fracture, patient age and method of fixation to provide clear outcomes that can be useful in clinical decision-making (Cha et al. 2023).

DL is proficient in picture-based prediction. Convolutional neural networks are able to automatically extract high-level features of radiographs, CT or MRIs and reveal signs of subtle healing without any labeling. Recurrent neural networks and long short memory units are better adapted to time-series data, for example, time-varying imaging trends or time-varying lab trends, allowing time-dependent healing modeling (Lin et al. 2023).

Unsupervised learning is less common but can identify hidden patterns without labeled data. Methods such as k-means clustering, hierarchical clustering and principal component analysis cluster patients together based on fracture characteristics, healing capacity or risk factors. These can guide the development of future models and improve understanding of patient heterogeneity (Liu et al. 2023).

Hybrid and ensemble approaches combine multiple models to enhance accuracy and robustness. For example, combining random forest with gradient boosting or integrating ML with deep networks can enhance performance and generalizability. These approaches help mitigate overfitting, which is particularly helpful for achieving reliable predictions in clinical practice (Yüce et al. 2025).

Compared to conventional tools, AI models have added benefits: they can handle multidimensional datasets of size, model nonlinear interactions between variables and give quantitative results. Still, some problems exist, including the need for extensive and high-quality data, overfitting and transparency of some DL models which complicates interpretability, exist (Karthik et al. 2025). In spite of these concerns, AI predictions have performed better than the traditional tests, which opens up the possibilities of a revolution in treating long bone fractures.

1.3. Data sources and predictive variables

The quality of the data and its diversity is crucial to the correctness of AI predictions. The demographics of the patient such as age, sex, BMI and comorbid conditions such as diabetes, osteoporosis, as well as smoking, dependably correlate with the healing results (Schulz et al. 2025). The age factor and some health conditions postpone bone regeneration; this is why such variables are necessary in predictive modeling.

The nature of the fracture greatly impacts union. Biological healing depends on variables, which include location, type (transverse, oblique, comminuted), degree of displacement and involvement of soft tissues (Takahashi et al. 2023). High energy or complex fractures are risk factors which predispose patients to delayed or non-union. Risk is stratified using AI models to inform treatment decisions.

Surgical specifics are the most essential factors of healing. Such variables as the fixation technique (intramedullary nailing, plating, external fixation) and the quality of reduction, as well as perioperative care, influence the outcome (Engels et al. 2024). This data can be incorporated into AI to assess the effect of surgical decisions on union and provide information upon which to determine the postoperative care or prompt intervention in the case of high-risk patients.

Visual images are a source of valuable information to AI prediction. X-rays, CTs and MRIs detect the fracture structure, callus, bridging of the cortical bone and bone density (Namireddy et al. 2024). Radiomics uses quantitative image features to create patterns that clinicians otherwise would have overlooked, thus increasing accuracy and objectivity.

Biochemical bone turnover markers, such as alkaline phosphatase, osteocalcin and C -terminal telopeptide, give insight into the bone physiology (Liu et al. 2024). Individual variability is also present, but integrating such markers with demographic, clinical and imaging data enhances AI performance, particularly for patients with complex comorbidities or bone metabolic imbalances.

1.4. Integration of imaging with AI

The key aspect of fracture assessment is medical imaging, and the combination of the latter with AI has led to a significant enhancement of fracture union predictions. The traditional methods of radiographs are the most accessible and least expensive forms of healing follow-up. Serial X-ray AI models may be used to identify otherwise hard-to-see evidence of callus formation and cortical bridging, which may be missed by a human viewer and thereby identify even delayed union early (Chen et al. 2025b).

Computed tomography (CT) provides three-dimensional images of a high-resolution view of the bone structure, fracture fragments and even the process of healing in detail. With the aid of AI algorithms, it is possible to analyze volumetric and textural features based on CT information, and such measures have been called the callus volume, bone mineral density and cortical continuity. Such objective measurements enhance the accuracy of fracture-healing measurements compared to traditional interpretation by itself (Chen et al. 2025a).

Magnetic resonance images (MRIs) are better in the assessment of soft-tissue involvement, bone-marrow edema and vascularization on the fracture site. DL algorithms will analyze MRI images to evaluate the bone and tissue in the area, and the results allow us to have a holistic understanding of factors aiming at affecting union (Capkin et al. 2025). AI can serve more comprehensive healing outcome prediction, especially when applied in conjunction with MRI data and clinical and demographic data, especially in cases of complex or high-risk fractures.

Radiomics: the methodical mining of quantitative imaging features – also known as Radiomics – is an effective method of combining AI with imaging data. Radiomic features present texture, shape, intensity and Einstein at the fracture site which is all associated with biological healing potential. Radiomics increases sensitivity and specificity of models when it is fed in together with ML algorithms, allowing early and precise predictability of union or non-union (Fang et al. 2025).

Altogether, AI-based imaging modality integration shifts the approach to both assessing and predicting subjects to a more sustainable, data-driven perspective. Radiographs, CT and MRI as a part of AI, are used to complement each other, and they are incorporated into AI-based prognoses to provide robust and individualized outcomes. Radiomics and DL technologies, specifically, will revolutionize the management of fractures because it will be possible to provide an accurate, timely and personalized approach to fracture management.

Table 1.1 presents AI models, data sources and predictive performances in long bone fracture union.

AI model category	**Representative algorithms**	**Primary Data inputs**	**imaging integration**	**Predicted outcomes**	**Reported performance trends**
Supervised machine learning	Random forest, SVM, gradient boosting, logistic regression	Demographics, comorbidities, fracture type, fixation method	Optional (radiographic features)	Union versus delayed/ non-union	Accuracy often >85%; good interpretability
Deep learning (image-based)	CNNs	Serial X-rays, CT, MRI	core input modality	Early union prediction, callus formation	High AUC (≈0.90+), reduced observer bias
Temporal models	RNNs, LSTM	Longitudinal imaging and lab data	Serial imaging	Healing progression over time	Improved dynamic prediction
Unsupervised learning	k-means, PCA, hierarchical clustering	Multidimensional clinical data	Not mandatory	Patient subgroup identification	Risk stratification support
Hybrid / ensemble models	RF + GBM, ML + DL combinations	Clinical + imaging + lab data	Strong integration	Robust union prediction	Reduced overfitting, higher generalizability
Radiomics-based AI	ML + radiomic features	Quantitative CT/MRI/X-ray features	Essential	Biological healing potential	Higher sensitivity and specificity

Table 1.1. *AI models, data sources and predictive performance in long bone fracture union*

1.5. Performance of AI models in predicting fracture union

AI models predictive of fracture union have been assessed in a number of studies and have proven to be significantly accurate and applicable in the clinical setting. ML algorithms including random forests and gradient boosting machines have demonstrated high predictive accuracy (often over 85%) in identifying patients likely to achieve timely union versus those at risk of delayed or non-union (Leister et al. 2023). These frameworks combine the multidimensional clinical, demographic and fracture-specific variables and provide strong predictions that are effective over traditional statistical methods.

Image-based predictions of fracture healing are best done using DL (CNNs, in particular). Recently, CNNs, trained on serial radiographs, CT or MRI images, are able to detect the initial signs of callus formation and cortical bridging, with great sensitivity and specificity in predicting fracture union (Erne et al. 2025). Other studies have given an area under the curve measurement of more than 0.90, which means that the discriminating ability is high. Notably, DL models automatically manipulate multifaceted imaging aspects, which lowers the use of manual interpretation and minimizes interobserver diversity.

Comparative studies involving AI models and conventional clinical evaluation reflect the superiority of AI models in predictive accuracy. Traditional systems, such as radiographic scoring systems and clinical assessment, do not usually have predictive capacity regarding early onset and are subject to analyst bias (Donié et al. 2024). On the contrary, AI can give objective, quantitative predictions, which can be used to stratify risks and intervene in time. Indicatively, patients who are identified by AI as high-risk non-union can be monitored closer or provided with additional treatment options, which may lessen complications and enhance results.

There are a number of clinical trials that demonstrated in practice the use of AI models in fracture management. Tibial and femoral fractures have shown high accuracy with the use of predictive models that combine patient demographics, fracture features, operation procedures and radiographic outcomes to predict union (Potty et al. 2023). These works show that it is possible to integrate AI-based decision support into orthopedic practice and present valid data on personalized predictive approaches to optimize patient care.

Altogether, there is high potential with AI models to predict fracture union due to their high accuracy, sensitivity and objective assessment of intricate data. Although issue such as data heterogeneity and model interpretability still exist, the presented performance of ML and DL models seems to indicate that AI can play a major role in improving the management of fracture and enhancing the outcomes of patients.

1.6. Challenges and limitations

The models of AI offer high potential in predicting the formation of a fracture, yet there are various obstacles that prevent them from being implemented on a regular basis in clinical practice. The quality and heterogeneity of the data that they are trained on is a significant problem. Dependable performance is necessary: the large and heterogeneous, high-quality datasets, and most studies are based on the small and single-centered sources, which are unlikely to be generalized (Raj et al. 2024). The variation in imaging protocols, patient demographics and the method of collection of data further complicates it and can be a source of bias in any prediction.

The second barrier is the inability to be interpreted. DL models are often regarded as a black box, and it is difficult for clinicians to understand why a specific prediction was arrived at (Park et al. 2024). This lowers trust and decreases acceptance. Explainable-AI techniques are still becoming available; however, there are few standard methods to use in fracture-prediction models.

There are also practical issues associated with the implementation of AI into practice. The models should be compatible with the available hospital information systems, PACS and EHRs (Raj et al. 2024). It needs deployment, hardware, staff training and also a change in workflow, which may be challenging in resource-constrained environments. Real-time decision support should be usable and accurate enough to not clutter the clinicians.

There are ethical, legal and privacy problems complicating the issues. Through AI, very sensitive patient data are usually handled, and this can be problematic in terms of confidentiality, security and consent (Wang et al. 2025). Medical AI regulations are in their development stages, and it is not clear how wrong predictions are liable. Fair performance in different populations is needed in order to prevent bias to exacerbate care disparities.

To conclude, AI has a chance to be used in predicting fracture union; however, addressing these issues is critical to use this technology safely and ethically in the clinic. Enhanced data quality, the creation of models that can be analyzed and uninterrupted integration of workflows as well as clear regulatory and ethical standards are the major steps that will enhance broader adoption in orthopedics.

1.7. Future directions

Future success will rely on large and multi-centered datasets. Obtaining data from a large number of institutions enhances the size of the sample, its diversity and applicability in a variety of settings and patient demographics (Gupta et al. 2025). These datasets generate powerful algorithms that work in clinical practice and minimize bias in single-center studies and increase clinical relevance.

It is also important to have explainable AI. Interpretability of models enhances trust in the clinicians and simplifies daily use. Such techniques as attention maps, feature-importance lists and model-agnostic frameworks assist clinicians to visualize what variables or imaging characteristics make predictions (Gupta et al. 2025). XAI enhances the trust and advances the clinical education.

Fractures can be changed with the help of AI, combining them with telemedicine and IoT devices. With remote patient monitoring and an AI analysis of imaging and clinical reports, it is possible to predict delayed union in a timely manner, minimize unnecessary visits and perform prompt intervention (Lin et al. 2025). Longitudinal mobility, load-bearing and adherence data may be included in wearable sensors and provide insights useful to predictive modeling and provide real-time individualized evaluation of the healing process.

Individualized forecasting models will transform orthopedic care. The combination of demographic, clinical, imaging and biochemical data can generate personalized healing curves and risk factors based on the AI models. These predictions would be used to make more specific interventions – when to start the weight-bearing, what should be fixed or whether adjunctive therapy is necessary, which benefits the outcomes and saves resources (Lin et al. 2025). Further research, extensive validation including external datasets, and close collaboration between clinicians and data scientists will be essential to unlock the full potential of AI in fracture union prediction.

1.8. Conclusion

Having accurate predictive capability for long bone healing is essential in enhancing patient outcomes, informing treatment choices, and reducing costs associated with delayed or failed healing. Conventional approaches using clinical evaluation, plain radiography, imaging and biochemical indicators are insufficient. They are not objective and are likely to vary, and in most cases are not able to predict the healing at an earlier stage. This is changing with the introduction of AI, as numerous data types, including patient demographics, fracture characteristics, surgical information, imaging features and laboratory findings, are integrated into models that provide objective and personalized decisions. All forms of ML supervised, DL and ensemble have demonstrated good potential in terms of predicting fracture union with precision, sensitivity and specificity. Convolutional neural networks and other forms of DL are capable of analyzing imaging data automatically. They also detect fine patterns that human eyes might overlook showing the extent to which the healing is taking place. Prediction is further enhanced by additional radiographs, CT scan and MRI, as well as radiomic features to AI workflows. This assists in time-based intervention and individual therapy. Yet, challenges persist. There is great variability in data, small sample sizes may be used, models may be black box, it is difficult to connect new workflows to practice and ethical issues come up. All these barriers will be overcome by multi-center datasets, explainable AI models, telemedicine connections and customizable predictive models. The clinical adoption of AI tools requires these steps to be taken. Overall, the capacity of AI to predict fracture union provides a perspective of improvement in orthopedics. They can improve the results, streamline the process of making decisions and advance personalized medicine in terms of a fracture management tool.

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