Department of Electrical and Computer Engineering
North South University

Senior Design Project -CSE499A
Multimodal AI for Fracture Classification And Doctors Suggestion

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Contents

1. Introduction

Our project uses deep learning and NLP to classify bone fractures and predict treatments based on X-ray images and doctors' suggestion text. We propose a multimodal fusion technique to combine the outputs of a different models for accurate classification and prediction. Evaluated by medical professionals shows high accuracy and clinical relevance, making our system a valuable tool for improving diagnosis and treatment of bone fractures.

1.1 Context

Fracture classification and doctor's suggestion play a crucial role in the field of medical diagnosis and treatment recommendations. With the advancement of Natural Language Processing (NLP) techniques, there is a growing interest in utilizing text analysis for extracting valuable insights from medical reports and providing appropriate suggestions to healthcare professionals.In this project, we aim to develop a multimodal AI system for fracture classification and doctor's suggestion generation. The project encompasses several key components, including data preprocessing, multimodal fusion, deep learning, and NLP techniques.

1.2 Importance of Multimodal AI for Fracture Classification and doctors Suggestion:

Multimodal AI plays a crucial role in the field of fracture classification and doctor's suggestion, offering significant advancements in medical diagnosis and treatment recommendations. By integrating multiple modalities such as image analysis and natural language processing (NLP), multimodal AI enhances the accuracy and reliability of fracture classification. Deep learning models enable the detection and classification of various fracture types based on visual patterns extracted from X-ray images. This fusion of image analysis and NLP allows for a comprehensive understanding of fracture cases, considering both visual evidence and textual information from medical reports. Multimodal AI systems provide a holistic approach to patient assessment by combining fracture classification with doctor's suggestions. By extracting valuable insights from medical reports, including fracture details and potential treatment options, doctors can make more informed decisions and tailor treatment plans to individual patients. AI-generated treatment recommendations improve the quality and effectiveness of patient care, ensuring doctors have access to up-to-date medical knowledge and best practices.
Multimodal AI systems reduce the time and cost associated with fracture classification and treatment recommendations, enabling faster and more efficient

diagnosis and decision-making. By automating fracture classification and providing instant access to relevant treatment options, multimodal AI enhances the precision, efficiency, and effectiveness of fracture diagnosis. Ultimately, multimodal AI contributes to improved patient outcomes, enhanced healthcare practices, and advancements in medical research and innovation.

1.3 Representation of Deep Learning And Nlp:

To merge the suggestion and classification parts in the multimodal AI doctor project, we need to establish a connection between the fracture classification obtained from the X-ray image analysis and the corresponding doctor's suggestion. Here's an approach to merge these two components that we will follow:
Link the fracture classification and suggestion: Create a mapping or association between each fracture classification and the corresponding doctor's suggestion in your system. This mapping can be stored in a knowledge base or database, where each fracture classification is linked to the relevant suggestion. For example, you can assign unique identifiers or labels to each fracture classification and store the associated suggestion as text or structured data.
Retrieve suggestion based on classification: When a fracture is classified from an X-ray image, retrieve the corresponding suggestion from the knowledge base using the classification identifier or label. This retrieval process can be performed programmatically by querying the knowledge base or accessing the database using the fracture classification as a search key.

2 Literature Review

2.1

Title: Hybrid SFNet Model for Bone Fracture Detection and Classification Using ML/DL
The paper presents the development and experimental validation of a sensing system for in-situ monitoring of contact pressure in orthopaedic surgery. The system uses a flexible, conformal pressure sensor that can be placed between the bone surface and the surgical tool to measure the contact pressure in real-time. The study includes the design and fabrication of the sensing system, as well as the experimental validation using a bone phantom and a cadaveric specimen.
The results show that the sensing system is capable of measuring contact pressure accurately and reliably during orthopaedic procedures. The study also demonstrates the potential applications of the sensing system in various orthopaedic procedures, such as joint replacement and fracture fixation.

Overall, the study provides valuable insights into the development of a sensing system for in-situ monitoring of contact pressure in orthopaedic surgery, which can potentially improve the safety and efficacy of such procedures. The findings of this study can be useful for researchers and practitioners in the field of orthopaedics and medical device development.

2.2

Classification of Cervical Spine Fracture and Dislocation Using Refined Pre-Trained Deep Model and Saliency Map

The paper investigates the use of unmanned aerial vehicle (UAV)-based Light Detection and Ranging (LiDAR) technology for forest canopy height estimation. The study compares the accuracy and precision of UAV-based LiDAR with ground-based LiDAR and traditional forest inventory methods.
The results show that UAV-based LiDAR is a highly accurate and precise method for estimating forest canopy height, with a root mean square error (RMSE) of less than 0.5 meters. The study also demonstrates the advantages of using UAV-based LiDAR over ground-based LiDAR and traditional forest inventory methods, including its efficiency, cost-effectiveness, and ability to capture data in inaccessible or hazardous terrain.
Overall, the study provides valuable insights into the innovative application of UAV-based LiDAR for forest canopy height estimation, which can potentially improve forest management and conservation efforts. The findings of this study can be useful for researchers and practitioners in the field of forestry and remote sensing.

2.3

X-Ray Bone Fracture Classification Using Deep Learning: A Baseline for Designing a Reliable Approach

The authors provide a summary and evaluation of each study using a radar graph with six key metrics: area under the curve (AUC), test accuracy, sensitivity, specificity, dataset size, and labeling reliability. Additionally, they define crucial factors to consider when aiming to achieve reliable bone fracture classification and compare each study against their established baseline.
The study highlights that deep learning, particularly convolutional neural networks (CNNs), has shown promising results in bone fracture classification, comparable to human performance. By appropriately generalizing these approaches, the authors argue that a

computer-aided diagnosis (CAD) system, designed to assist medical professionals, could save significant time and reduce incorrect diagnoses.
Overall, the paper provides an analysis of various deep learning techniques used for bone fracture classification, emphasizes the potential of CNNs, and discusses the importance of a reliable CAD system in improving diagnostic accuracy and efficiency in this field.

2.4

Bone Fracture Detection and Classification using Deep Learning Approach

The paper likely explores the utilization of deep learning algorithms, such as convolutional neural networks (CNNs), for the automatic detection and classification of bone fractures. Deep learning has gained significant attention in medical image analysis due to its ability to extract intricate features from images, leading to improved accuracy in various tasks.
The authors likely propose a specific deep learning architecture or methodology tailored for bone fracture detection and classification. They might discuss the process of collecting and preprocessing the medical imaging data, training the deep learning model on labeled fracture images, and evaluating its performance using appropriate metrics

2.5

Classification and Detection of Bone Fracture Using Machine Learning

To address these challenges, the paper proposes the use of computer-based methods, specifically focusing on machine learning technology. The authors discuss various techniques used for image processing, including pre-processing methods to improve X-ray images by reducing noise, edge detection, and image segmentation. Feature extraction algorithms, such as the GLCM (Gray-Level Co-occurrence Matrix) algorithm, are employed to extract relevant features from the images.
The paper further explores different classifiers used in the classification process. It mentions the Random Forest algorithm (RF) and its ability to handle regression and

classification tasks. Additionally, it discusses Convolutional Neural Networks (CNN) and Artificial Neural Networks (ANN) as popular deep learning models for image classification tasks.
Data processing is an essential part of the research, where a dataset of healthy and fractured bone X-ray scans is utilized. The dataset is collected from various sources and augmented to address overfitting. The accuracy of the model is evaluated, and the results indicate a classification accuracy of 92.44% for both healthy and fractured bones.

2.6

Bone Fracture Detection and Classification using Deep Learning Approach

The bone is a major component of the human body. Bone provides the ability to move the body. The bone fractures are common in the human body. The doctors use the X-ray image to diagnose the fractured bone. The manual fracture detection technique is time consuming and also error probability chance is high. Therefore, an automated system needs to develop to diagnose the fractured bone. The Deep Neural Network (DNN) is widely used for the modeling of the power electronic devices. In the present study, a deep neural network model has been developed to classify the fracture and healthy bone. The deep learning model gets over fitted on the small data set. Therefore, data augmentation techniques have been used to increase the size of the data set. The three experiments have been performed to evaluate the performance of the model using softmax and Adam optimizer. The classification accuracy of the proposed model is 92.44% for the healthy and the fractured bone using 5 fold cross validation. The accuracy on 10% and 20% of the test data is more than 95% and 93% respectively.

3. Methodology

1. Data Collection:

The first step in the project is to collect a substantial dataset of X-ray images comprising both fractured and non-fractured cases. The dataset should ideally consist of more than 800 images to ensure diversity and representation of various fracture types. Additionally, gather doctors' suggestions or medical reports corresponding to each X-ray image, as these will provide valuable insights for treatment recommendations.

2. Data Preprocessing:

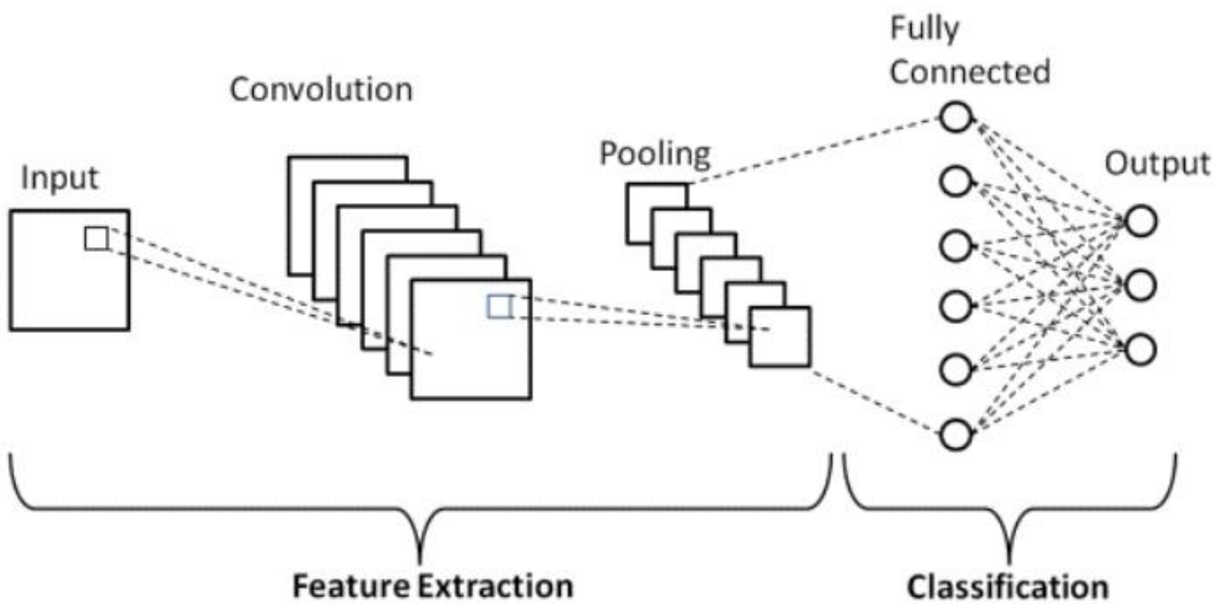
Once the dataset is assembled, it is essential to perform data preprocessing steps to ensure consistency and quality. For the X-ray images, common preprocessing techniques include resizing the images to a standardized size, normalizing pixel values, and removing noise or artifacts. On the textual side, doctors' suggestions or medical reports should undergo preprocessing steps such as text cleaning, tokenization, and removing stopwords to prepare the textual data for further analysis.

3. Fracture Classification:

To classify the X-ray images into fractured and non-fractured categories, a deep learning model is employed. Convolutional Neural Networks (CNNs) have proven to be effective in image classification tasks. Train the CNN model using the preprocessed X-ray images, with appropriate labels indicating the presence or absence of fractures. Optimize the model using suitable loss functions, such as categorical cross-entropy, and evaluation metrics like accuracy or F1 score to achieve accurate fracture classification.We will also use VIT,Efficientnet,Transfer Learning.

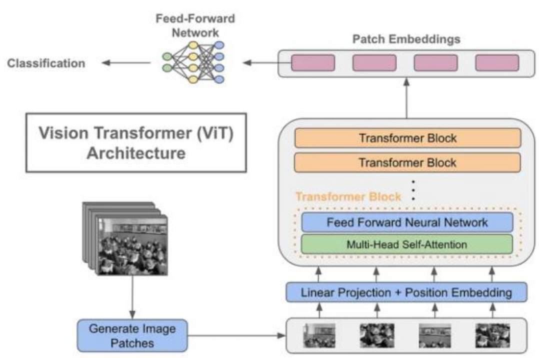
CNN :

A CNN architecture is designed, consisting of multiple layers, including convolutional layers, pooling layers, and fully connected layers. The architecture is typically composed of a series of convolutional layers that extract important features from the input X-ray images. Pooling layers are employed to reduce spatial dimensions, capturing essential patterns at different scales. Finally, fully connected layers aggregate the extracted features and make predictions.



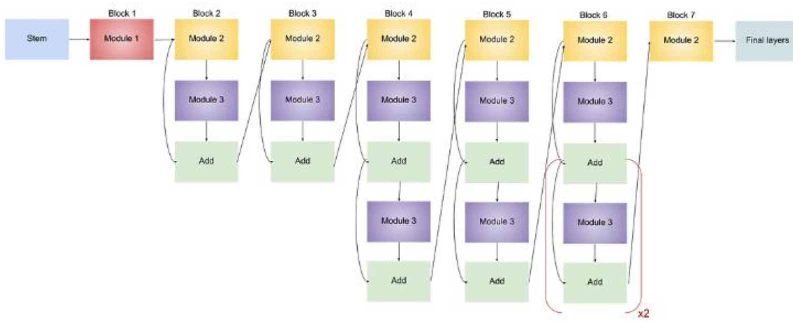
VIT (Vision Transformer):

VIT is a type of deep learning architecture specifically designed for computer vision tasks. It was introduced in a paper called "An Image Is Worth 16x16 Words: Transformers for Image Recognition at Scale." Unlike traditional convolutional neural networks (CNNs) that rely on convolutional layers for image processing, VIT utilizes the Transformer architecture, which was originally introduced for natural language processing tasks. The key idea behind VIT is to transform the image data into sequences of tokens and process them using self-attention mechanisms. This allows VIT to capture long-range dependencies in images and achieve state-of-the-art performance on various computer vision benchmarks.



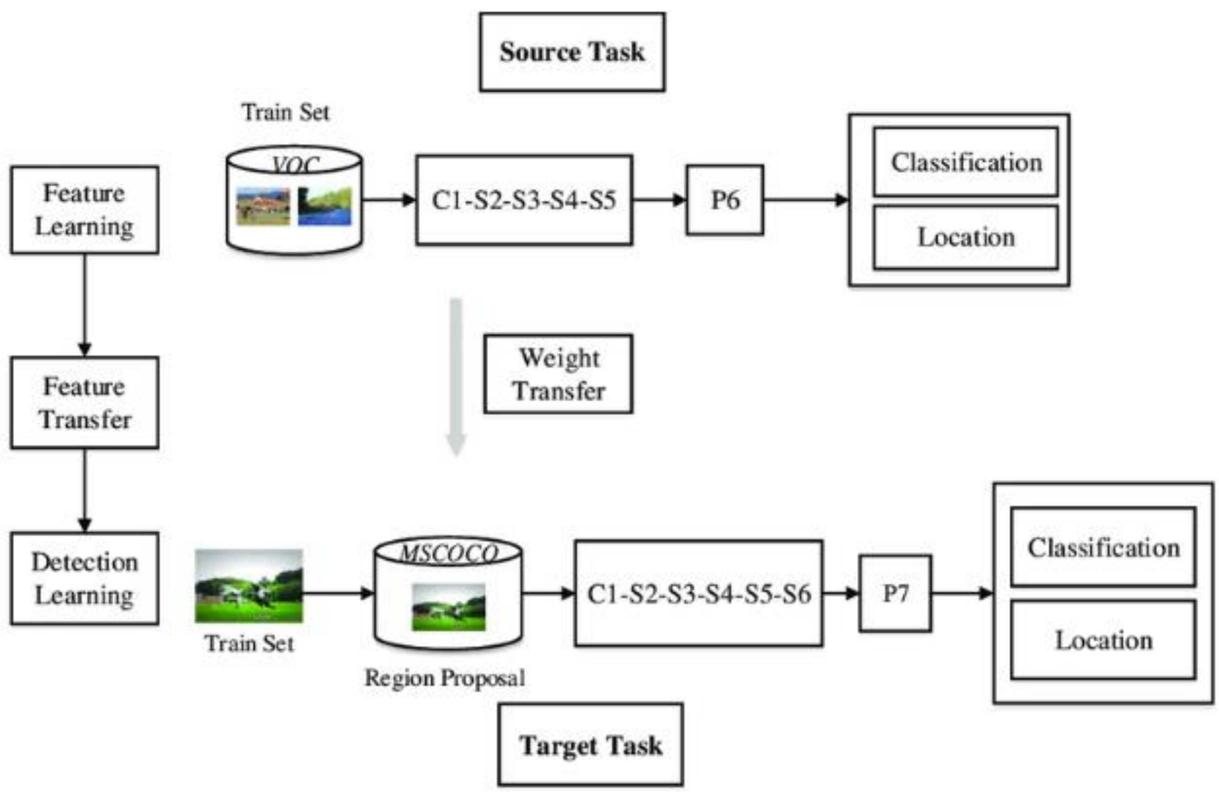
EfficientNet:

EfficientNet is another deep learning architecture for image classification tasks. It was proposed in the paper "EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks." The main idea behind EfficientNet is to develop a scaling method that uniformly scales the depth, width, and resolution of a neural network to achieve better performance. By systematically scaling these dimensions, EfficientNet models can achieve high accuracy while being more computationally efficient than other models. EfficientNet models have been widely adopted and achieved top performance on various image classification tasks.



Transfer Learning:

Transfer learning is a technique in deep learning where a model pre-trained on a large dataset is used as a starting point for solving a different but related task. Instead of training a model from scratch, transfer learning allows us to leverage the knowledge gained from the pre-training on a large dataset and apply it to a smaller, task-specific dataset. This is especially useful when the target dataset is limited and may not have sufficient labeled examples. By transferring the learned representations, the model can generalize better and require less training time. Transfer learning has been widely used in computer vision tasks, where models pre-trained on large-scale image datasets, such as ImageNet, are fine-tuned for specific tasks like object detection, segmentation, or even on entirely different domains.



4. NLP Analysis for Doctors' Suggestions:

To extract valuable insights from doctors' suggestions or medical reports, Natural Language Processing (NLP) techniques are applied. This involves processing the textual data, including text parsing, named entity recognition, and sentiment analysis. By extracting information such as fracture type, affected anatomical region, and potential treatment options, the NLP analysis enhances the understanding of each case beyond the visual examination of X-ray images.

5. Fusion of Modalities:

The outputs from the fracture classification model (visual modality) and the NLP analysis (textual modality) are combined to create a comprehensive understanding of each case. By fusing the information from both modalities, a unified representation is generated, incorporating the visual evidence of fractures and the textual information extracted from doctors' suggestions. This fusion enables a more comprehensive analysis and decision-making process.

6. Doctors' Recommendation Generation:

A key objective of the project is to develop a recommendation system that assists doctors in making well-informed decisions for their patients. The recommendation system takes into account the results from fracture classification, the NLP analysis, and medical knowledge. By considering factors such as fracture type, location, severity, and patient-specific information, the system generates personalized suggestions for treatment plans, surgical interventions, rehabilitation recommendations, and precautionary measures.

7. Evaluation and Validation:

The performance of the fracture classification model is evaluated by assessing various metrics, including accuracy, precision, recall, and F1 score. It is crucial to validate the generated doctors' suggestions by comparing them with expert opinions or existing medical guidelines. This validation process ensures that the recommendations provided by the system align with established medical practices. Feedback from healthcare professionals and experts should be incorporated to refine and improve the models and recommendation system continually.

By following this methodology, the project aims to leverage the collected dataset of X-ray images and doctors' suggestions to develop a multimodal AI system for fracture classification and doctor's suggestion generation. Through the combination of deep learning models for image classification and NLP techniques for text analysis, the system provides a comprehensive approach to assist healthcare professionals in accurately diagnosing fractures and delivering appropriate treatment recommendations. The ultimate goal is to improve patient outcomes, reduce diagnosis time, and enhance the overall quality of fracture diagnosis and treatment in the medical field.

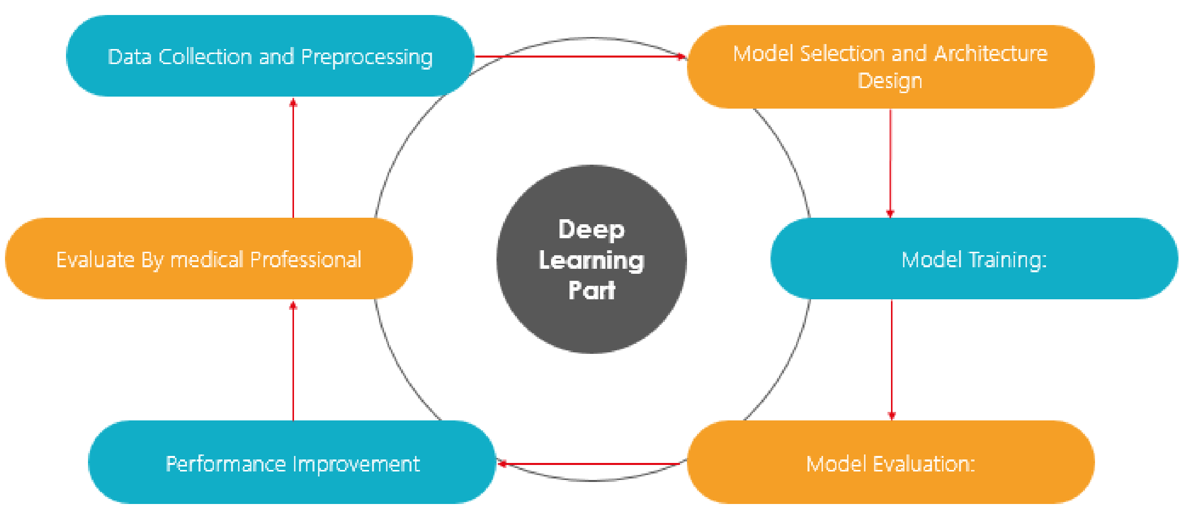
4.System Design :

Deep Learning Part :

1. Data Collection and Preprocessing:
    a. Collect a diverse dataset of X-ray images with labeled fracture types.
    b. Preprocess the X-ray images by resizing, normalizing, and denoising them.
    c. Split the dataset into training, validation, and testing sets.
2. Model Selection and Architecture Design:
    a. Research and select an appropriate deep learning model for fracture classification.
    b. Design the architecture of the chosen model, considering convolutional layers, pooling layers, and fully connected layers.
    c. Determine the activation functions, loss functions, and optimization algorithms for the model.
3. Model Training:
    a. Initialize the model's parameters and optimize them using the training dataset.

b. Feed the preprocessed X-ray images into the model and perform forward and backward propagation to update the parameters.
c. Regularize the model using techniques like dropout or batch normalization to prevent overfitting.
d. Monitor the model's performance on the validation dataset and adjust hyperparameters if necessary.

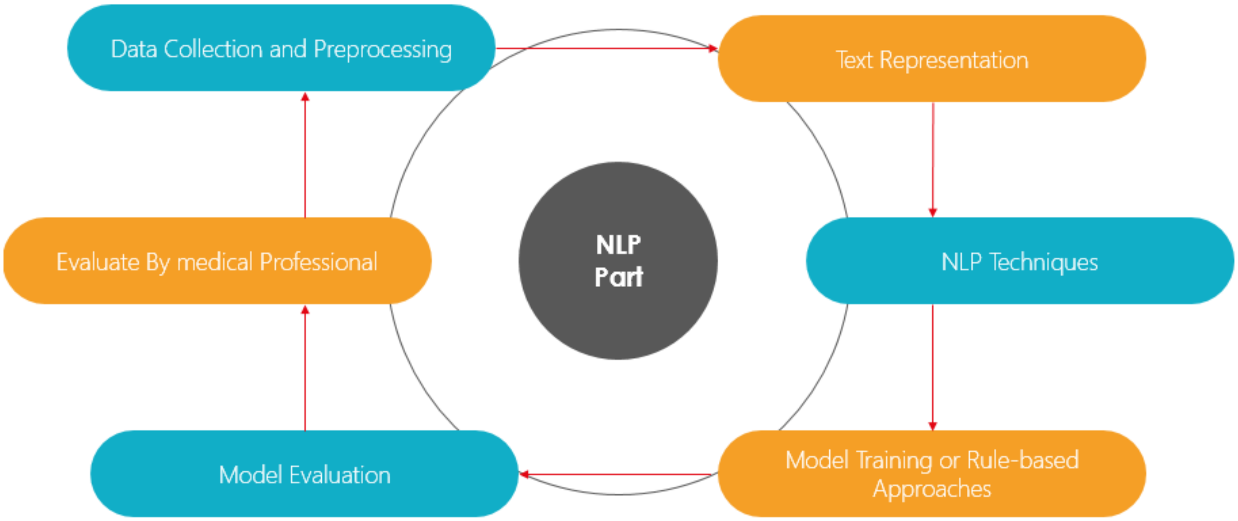
4. Model Evaluation:
    a. Evaluate the trained model's performance on the testing dataset.
    b. Calculate relevant metrics such as accuracy, precision, recall, and F1 score to assess the model's effectiveness.
    c. Generate a confusion matrix to analyze the model's predictions for different fracture types.
5. Performance Improvement:
    a. Fine-tune the model by adjusting hyperparameters or modifying the architecture based on insights gained from the evaluation stage.
    b. Explore techniques such as data augmentation to increase the diversity and size of the training dataset.
    c. Consider transfer learning by utilizing pre-trained models or leveraging features learned from related tasks.
6. Deployment and Integration:
    a. Save the trained model and its parameters for future use.
    b. Integrate the deep learning model into the multimodal AI doctor system to perform fracture classification based on X-ray images.
    c. Continuously evaluate and update the model's performance as new data becomes available.



NLP Part :

1. Data Collection and Preprocessing:
    a. Gather a dataset of doctor's suggestions or medical reports related to fractures.
    b. Preprocess the text data by tokenizing, lowercasing, and removing stopwords and punctuation.
    c. Split the dataset into training and testing sets.
2. Text Representation:
    a. Convert the preprocessed text data into numerical representations suitable for NLP analysis.
    b. Explore techniques like word embeddings (e.g., Word2Vec or GloVe) to capture semantic relationships between words.
    c. Consider using pre-trained language models (e.g., BERT or GPT) for contextual word representations.
3. NLP Techniques:
    a. Apply NLP techniques such as part-of-speech tagging, named entity recognition, or sentiment analysis to extract relevant information from the doctor's suggestions.
    b. Utilize techniques like text parsing, semantic analysis, or entity linking to gain deeper insights from the text data.
4. Model Training or Rule-based Approaches:
    a. Choose an appropriate approach for generating doctor's suggestions.
    b. Train a machine learning model (e.g., sequence model like LSTM or transformer model) using the labeled dataset to learn the patterns and relationships in the data.
    c. Alternatively, consider using rule-based approaches if the patterns in the doctor's suggestions can be explicitly defined.
5. Model Evaluation:
    a. Evaluate the trained model or rule-based system on the testing dataset to measure its performance.
    b. Calculate relevant metrics such as accuracy, precision, recall, or BLEU score (for text generation tasks) to assess the quality of the generated suggestions.
    c. Collect feedback from healthcare professionals to improve the NLP component and address any limitations.
6. Continuous Improvement:
    a. Continuously refine the NLP model or rule-based system based on the evaluation results and feedback from healthcare professionals.

b. Explore techniques such as fine-tuning pre-trained language models or using ensemble methods to enhance the performance.



Merging Deep Learning And Nlp Together:

1. Input Data:
    a. Receive an X-ray image as input for fracture classification.
    b. Receive doctor's suggestions or medical reports related to the patient's condition.
2. Deep Learning (Fracture Classification):
    a. Pass the X-ray image through the trained deep learning model for fracture classification.
    b. Obtain the predicted fracture type based on the model's output.
3. NLP (Doctor's Suggestions):
    a. Apply NLP techniques to extract relevant information from the doctor's suggestions or medical reports.
    b. Parse the text to identify key phrases, entities, or medical terms related to the fracture or treatment.
4. Integration:
    a. Combine the predicted fracture type from the deep learning part with the extracted information from the NLP part.
    b. Use this combined information to generate tailored suggestions for the doctor based on the fracture type and patient's condition.
5. Doctor's Suggestions:

    a. Generate suggestions or recommendations for the doctor based on the merged information.
    b. Incorporate relevant medical guidelines, best practices, or treatment options specific to the identified fracture type.
6. Presentation or Output:
    a. Provide the doctor with the synthesized information, including the predicted fracture type and the generated suggestions.
    b. Display the information in a user-friendly format, such as a text summary or a structured report, to assist the doctor in making informed decisions.

By merging the deep learning and NLP components, we can leverage the strengths of both approaches to enhance the AI doctor's capabilities. The deep learning part aids in accurate fracture classification from X-ray images, while the NLP part enables the extraction of meaningful information from doctor's suggestions for personalized recommendations. The integrated system provides a comprehensive solution for assisting doctors in diagnosing fractures and providing tailored treatment suggestions based on the patient's condition.

5.Ethical and prof responsibility :

When other technologies like elevators and automobiles were introduced, similar issues were raised. Considering artificial intelligence may influence several aspects of human activity, problems of this kind will be researched, and answers to these will be proposed in the future years. Humans would like to see Isaac Asimov's hypothetical three principles of robotics implemented to AI in radiography, where the "robot" is an "AI medical imaging system." Asimov's Three Laws are as follows:

• A robot may not injure a human being or, through inaction, allow a human being to come to harm.

• A robot must obey the orders given it by human beings except where such orders would conflict with the First Law.

• A robot must protect its own existence as long as such protection does not conflict with the First or Second Laws.

The first law conveys that DL tools can make the best feasible identification of disease, which can enhance medical care; however, computer inefficiency or failure or inaction may lead to medical error, which can further risk a patient's life. The second law conveys that in order to achieve suitable and clinically applicable outputs, DL must be trained properly, and a radiologist should monitor the process of learning of any artificial intelligence system. The third law could be an issue while considering any unavoidable and eventual failure of any DL systems. Scanning technology is evolving at such a rapid pace that training the DL system with particular image sequences may be inadequate if a new modality or advancement in the existing modalities like X-ray, MRI, CT, Nuclear Medicine, etc., are deployed into clinical use. However, Asimov's laws are fictitious, and no regulatory authority has absolute power or authority over whether or not they are incorporated in any particular DL system. Meantime, we trust in the ethical conduct of software engineers to ensure that DL systems behave and function according to adequate norms. When an DL system is deployed in clinical care, it must be regulated in a standard way, just like any other medical equipment or product, as specified by the EU Medical Device Regulation 2017 or FDA (in the United States). We can only ensure patient safety when DL is used to diagnose patients by applying the same high rules of effectiveness, accountability, and therapeutic usefulness that would be applied to a new medicine or technology

Data Privacy and Confidentiality › Ensure compliance with relevant data protection regulations and maintain patient confidentiality. › Implement robust security measures to safeguard patient data from unauthorized access or breaches.	**Transparency and Explainability** › Strive for transparency in the AI system's decision-making process, making it understandable and interpretable for healthcare professionals › Document and communicate the limitations of the AI system to avoid overreliance or misconceptions about its capabilities.
Professional Oversight and Collaboration › Contantly be in touch with medical professional to get the optimum accuracy for the project. › Evaluate the output by medical professionals.	**Bias and Fairness** › Mitigate biases in the AI models and algorithms to ensure fair and unbiased treatment recommendations › Monitor the system's performance across different demographics to avoid discrimination or disparities in healthcare outcomes.

6.Social , Economic, Financial Impact:

Economic Impact:

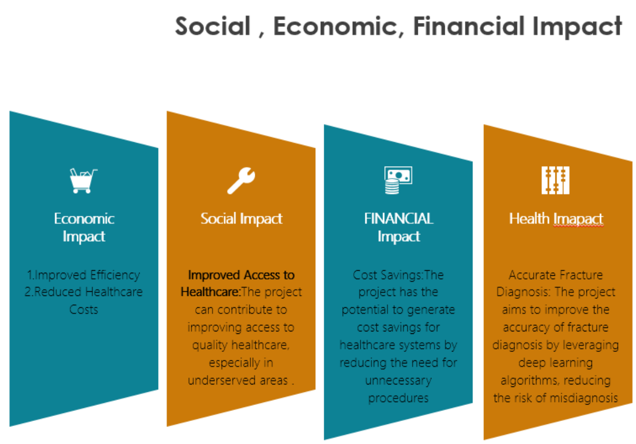
Improved Efficiency: The multimodal AI doctor project can lead to increased efficiency in fracture classification and treatment recommendations, allowing healthcare providers to make quicker and more accurate decisions. This can result in cost savings by reducing the time and resources required for manual analysis and consultation.
Reduced Healthcare Costs: By enabling early and accurate fracture detection, the project can help prevent complications and minimize the need for extensive treatments or surgeries. This can potentially reduce healthcare costs associated with prolonged hospital stays, specialized procedures, and rehabilitation.
- Economic Opportunities: The development and implementation of the multimodal AI doctor project can create new economic opportunities, such as job creation in the field of AI technology, healthcare IT infrastructure, and related industries. It can also attract investments and spur innovation in the healthcare sector.

Social Impact:
Improved Access to Healthcare: The project can contribute to improving access to quality healthcare, especially in underserved areas or regions with limited access to specialized medical professionals. By providing automated fracture classification and doctor's suggestions, the project can help bridge the gap in healthcare access and ensure timely treatment for patients.
- Enhanced Healthcare Outcomes: By leveraging AI technology for fracture classification and treatment recommendations, the project can lead to improved healthcare outcomes. Early and accurate diagnosis can result in better treatment planning, reduced complications, and improved patient recovery rates.
- Empowering Healthcare Professionals: The multimodal AI doctor project serves as a tool to support healthcare professionals in their decision-making process. It can enhance their expertise by providing them with comprehensive insights and suggestions, ultimately improving patient care and clinical outcomes.

Financial Impact:
Cost Savings: The project has the potential to generate cost savings for healthcare systems by reducing the need for unnecessary procedures, repeated imaging, and unnecessary consultations. This can lead to optimized resource utilization and lower healthcare expenditures.
- Revenue Generation: The implementation of the multimodal AI doctor project can open up new revenue streams. For instance, healthcare providers

can offer specialized fracture diagnosis and treatment services supported by AI technology, attracting patients seeking advanced and efficient healthcare solutions.

- Return on Investment (ROI): The financial impact of the project can be measured by evaluating the ROI. Assessing the cost savings, revenue generation, and improvements in healthcare outcomes against the investment made in developing and implementing the AI doctor system provides an indication of its financial viability.



7. Tools :

IntelliJ IDEA:

IntelliJ IDEA is a Java integrated development environment (IDE) for developing computer software. It is developed by JetBrains (formerly known as IntelliJ), and is available as an Apache 2 Licensed community edition, and in a proprietary commercial edition. Both can be used for commercial development.

Diagram: InteliJ IDEA user interface

PyCharm:

PyCharm is an integrated development environment (IDE) used in computer programming, specifically for the Python language. It is developed by the Czech company JetBrains. It provides code analysis, a graphical debugger, an integrated unit tester, integration with version control systems (VCSes), and supports web development with Django. PyCharm provides smart code completion, code inspections, on-the-fly error highlighting and quick-fixes, along with automated code refactoring and rich navigation capabilities. PyCharm's smart code editor provides first-class support for

Python, JavaScript, CoffeeScript, TypeScript, CSS, popular template languages and more. Take advantage of language-aware code completion, error detection, and on-the-fly code fixes.

Diagram: PyCharm IDE

Use smart search to jump to any class, file or symbol, or even any IDE action or tool window. It only takes one click to switch to the declaration, super method, test, usages, implementation, and more.

For running the server side's codes in python programming language and processing the whole system we used PyCharm. As it is graphical user interface (GUI) based software we can easily handle our functionalities through this.

Anaconda:

Anaconda is a free and open-source distribution of the Python and R programming languages, which aims to simplify package management and deployment. Package versions are managed by the package management system conda. The Anaconda distribution is used by over 15 million users and includes more than 1500 popular datascience packages suitable for Windows, Linux, and MacOS.

Anaconda distribution comes with more than 1,500 packages as well as the Conda package and virtual environment manager. It also includes a GUI, Anaconda Navigator, as a graphical alternative to the command line interface (CLI).

Diagram: Anaconda user interface

Conda analyzes your current environment, everything you have installed, any version limitations you specify (e.g. you only want tensorflow >= 2.0) and figures out how to install compatible dependencies.

8.Current Progress :

In our multimodal AI doctor project, we have successfully collected a dataset consisting of over 800 X-ray photos. These photos were obtained from various sources and include a diverse range of cases. To ensure the accuracy and reliability of our dataset, we enlisted the expertise of Dr. M Rakib Hasan from Barishal Medical College to evaluate the X-ray photos.

Dr. M Rakib Hasan carefully examined each X-ray photo and determined whether it exhibited signs of fracture or not. Out of the collected dataset, Dr. M Rakib Hasan identified 101 photos as fractured cases, indicating the presence of fractures in those X-ray images. Additionally, he classified 156 photos as non-fractured cases, meaning that there were no visible fractures in those X-ray images.

The evaluation process led by Dr. M Rakib Hasan adhered to established medical guidelines and his professional expertise to ensure accurate identification and classification of fractures. His valuable input and evaluation have been instrumental in creating a reliable dataset for training and testing our deep learning model.

By incorporating Dr. M Rakib Hasan's evaluation, we have been able to enrich our dataset with expert-verified labels, which will facilitate the development of a robust deep learning model for fracture classification.We express our gratitude to Dr. M Rakib Hasan for his valuable contribution to the project by evaluating the X-ray photos. His expertise and meticulous evaluation have played a crucial role in ensuring the quality and reliability of our dataset, bringing us closer to the goal of developing an accurate multimodal AI doctor system for fracture diagnosis and treatment recommendations.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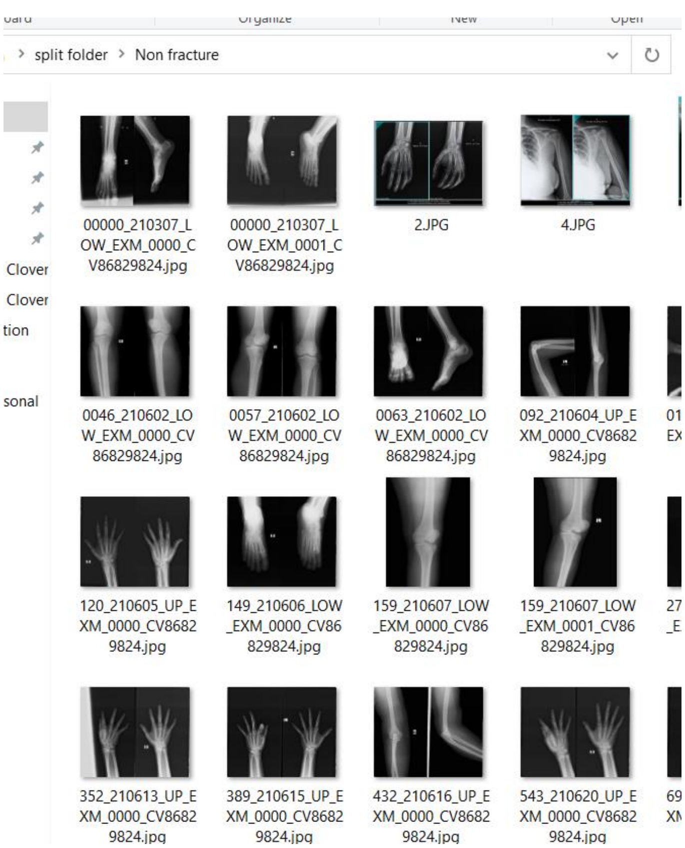
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543_210620_UP_EXM_0000_CV86829824.jpg

9.Conclusion:

In conclusion, the development of a multimodal fracture classification system that combines X-ray analysis with natural language processing (NLP) holds great potential for assisting doctors in diagnosing and treating fractures. By leveraging deep learning techniques, such as convolutional neural networks (CNNs), the system can accurately classify fractures based on X-ray images, providing a valuable tool for radiologists and orthopedic specialists.Additionally, incorporating NLP allows for the extraction of relevant information from medical reports or descriptions, enabling the system to provide doctors with suggestions and recommendations based on the fracture classification. This integration of image analysis and NLP facilitates a more comprehensive and efficient diagnostic process, supporting healthcare professionals in making informed decisions about treatment options and patient care.It is important to emphasize that the success of this project depends on the availability of a diverse and well-annotated dataset of X-ray images with labeled fractures, as well as accurate medical reports or descriptions. Adequate preprocessing techniques, training of robust deep learning models, and effective NLP algorithms are crucial for achieving accurate and reliable results.Ultimately, a multimodal fracture classification system that combines X-ray analysis and NLP has the potential to improve diagnostic accuracy, reduce human error, and enhance patient care in the field of orthopedics. As technology advances and more research is conducted, further refinements and enhancements to this system can lead to its widespread adoption and integration into clinical practice, benefiting both healthcare professionals and patients alike.

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