A Deep Learning Customized Framework for Spine Metastatic Bone Cancer Detection and Classification Based on Hierarchical Fuzzy Model

By
Md. Mezbaul Haque
213-15-4512

FINAL YEAR DESIGN PROJECT REPORT

This Report Presented in Partial Fulfillment of the Requirements for the **Degree of Bachelor of Science in Computer Science and Engineering**

Supervised by

Mr. Golam Rabbany
Lecturer
Department of Computer Science and Engineering Daffodil International University

Co-Supervised by

Md. Sazzadur Ahamed
Assistant Professor
Department of Computer Science and Engineering Daffodil International University

DAFFODIL INTERNATIONAL UNIVERSITY
Dhaka, Bangladesh
September 17, 2025

APPROVAL

This Project titled **"A Deep Learning Customized Framework for Spine Metastatic Bone Cancer Detection and Classification Based on Hierarchical Fuzzy Model"**, submitted by Md. Mezbaul Haque, ID No: **213-15-4512** to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on **17 September, 2025**.

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Faculty of Science & Information Technology
Daffodil International University

Dr. Md. Arshad Ali **External Examiner**
Professor
Department of Computer Science and Engineering
Hajee Mohammad Danesh Science & Technology University

DECLARATION

We hereby declare that this project has been done by us under the supervision of **Mr. Golam Rabbany, Lecturer**, Department of Computer Science and Engineering, Daffodil International University. We also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree or diploma.

Supervised by:

Mr. Golam Rabbany
Lecturer
Department of Computer Science and Engineering
Daffodil International University

Co-Supervised by:

Md. Sazzadur Ahamed
Assistant Professor
Department of Computer Science and Engineering
Daffodil International University

Submitted by:

Mezba

Md. Mezbaul Haque
Student ID: 213-15-4512
Department of Computer Science and Engineering
Daffodil International University

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ABSTRACT

Spinal metastatic bone cancer is a severe complication of advanced cancer like lung, breast, and prostate, so its early diagnosis and correct classification should be crucial to enhance treatment planning, decision-making, and patient survival. Conventional methods of diagnosis based on manual assessment of MRI and CT are rather slow and subject to error, with the necessity to adopt the use of computers. In this research, a customized deep learning framework is proposed that integrates the You Only Look Once (YOLO) family of object detection models with a hierarchical fuzzy inference system to detect and classify spinal lesions in CT scans. The Cancer Imaging Archive (TCIA) was utilized as the source of the dataset of 1,367 CT images, which were provided as DICOM data, we carefully preprocessed the data and converted into PNG and annotated into three categories: Normal, Lytic and Blastic. Multiple YOLO versions (YOLOv8, YOLOv5, YOLOv9, YOLOv10, YOLOv11, and YOLOv12) were trained and evaluated under a uniform experimental setup, and performance was assessed using precision, recall, F1-score, and mean Average Precision (mAP). It was comparatively analyzed that YOLOv11 completed the stable results by providing a precision of 89.1% and recall of 85.8% in comparison to the previous versions of YOLO. And then, YOLOv11 was modified with Fuzzy logic based upon the need to consider uncertain situations and the use of rules and membership functions to modify the predictions assisted in turning the classifications more sure and easier to comprehend. The hybrid YOLO with Fuzzy system obtained a total accuracy of 93.69% that showed improved diagnostic performance over the baseline YOLO models. We applied the fuzzy logic as a post processing layer for handle uncertain result. The framework helps doctors make better decisions, reduces errors, speeds up diagnosis, and supports earlier treatment of spinal metastatic bone cancer.

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Chapter 1

Introduction

This chapter presents a summary of the research, describing its motivation, aims, methods, results, and the general layout of the report.

1.1 Introduction

Spinal metastatic bone cancer is a medical emergency that usually develops in a patient with an advanced cancer such as lung, prostate, or breast cancer. These metastases can severely affect the vertebral column, leading to pain, instability, spinal cord compression, and, in many cases, permanent neurological damage if not diagnosed at an early stage [10]. Accurate and timely identification is therefore essential. However, conventional diagnostic approaches including CT scans, MRI, and bone scintigraphy are highly dependent on radiologists manual interpretation. It is labor intensive, time consuming and human error is likely to occur [11]. The use of advanced imaging techniques like PET/CT has enhanced detection but is still expensive, not widely available and requires expert analysis [12].

The fast growth of artificial intelligence (AI), especially deep learning, has opened new possibilities for automating cancer detection and classification. The YOLO object detection framework has gained wide attention in medical imaging for its ability to perform real-time detection with both high speed and accuracy [1]. Research shows that YOLO and other deep learning methods can work very well when trained with labeled medical datasets [6].

In this research, a dataset of 1,367 spinal CT scan images was collected from The Cancer Imaging Archive (TCIA). The DICOM images were first preprocessed, then converted to PNG, and finally labeled in YOLO format using Makesense AI. Multiple YOLO versions—YOLOv12, YOLOv11, YOLOv10, YOLOv9, YOLOv8, and YOLOv5—were trained and evaluated. Among these models, YOLOv11 gave the best results for accuracy, precision, and recall, so it was chosen as the baseline model for this framework. The YOLO model identifies possible problem areas in the spine by dividing the image into small grids and predicting the bounding boxes along with their classes in one go.

YOLO models are more effective but can generate uncertain predictions when lesion boundaries overlap or quality of the image is less. To provide a solution to this difficulty, a decision layer was added with YOLOv11, which employed a fuzzy logic. Fuzzy inference systems are designed to resemble human-type reasoning to refine predictions of uncertainty based on pre-defined membership functions and hierarchies. This can assist the system to better deal with the uncertainty during classification and increase the consistency of the results.

The referred YOLO + Fuzzy hybrid structure has been trained and evaluated on the basis of some standard performance indicators, such as confusion matrices, precision, recall, accuracy, and F1-score. As experimental research indicates, the addition of fuzzy logic and

YOLOv11 results in a more robust and accurate model relative to baseline YOLOs.
It is a powerful framework, with the potential to be a useful computer-aided tool, which helps the radiologists detect the spinal metastatic bone cancer early, diagnose faster, and provide better treatments to patients.

1.2 Motivation

This research is inspired by the increasing need to practice the early and precise diagnosis of spinal metastatic bone cancer as this is the way to achieve higher treatment outcomes and to prevent life threatening complications. The presence of spinal metastases is usually a big problem in cancer patients at an advanced stage like lung, breast or prostate cancer, which may cause severe back pain, compression of the nerve and eventual disability unless early detected. In most cases, these metastatic lesions go undetected until a critical phase develops which lowers treatment efficacy and tends to pose greater health risks to the patient.
Deep learning-based object detection models have turned out to be very helpful in the last few years and automatic defect detection and classification in medical images. As a real-time object detector, YOLO has been shown to have very good performance with regard to spinal lesion detection and classification in the field of medicine implementations [3]. But yet, even the most accurate YOLO models can provide ambiguous results in particularly low-quality images or overlapping bore boundaries. This is the cause why So called fuzzy logic systems are being adopted and this will be able to handle uncertainty and reason like human beings to rule out the vague predictions [2].
The solution to these issues is suggested in this study, which is to establish an intelligent hybrid system, involving YOLO-based detection along with hierarchical refinement of the fuzzy logic of the decisions made. This system facilitates early detection of spinal lesions, and improves classification of various types of cancer Normal, Lytic, and Blastic. Personally, this project allowed implementing deep learning on a real-life medical issue and to develop a practical system that can help healthcare professionals with early diagnosis. It has also allowed a certain interest in ongoing studies on AI-based healthcare innovation that can influence patient outcomes positively.

1.3 Objectives

- To develop a YOLO-based deep learning system for accurate and efficient detection of spinal metastatic lesions.
- To design a deep learning framework integrated with a Hierarchical Fuzzy Model for improved accuracy in spine metastatic bone cancer detection.

1.4 Methodology

The proposed study uses a structured, multi-step approach to build an intelligent deep learning system for detecting and classifying spinal metastatic bone lesions. The process

begins with the acquisition of spinal CT images from The Cancer Imaging Archive (TCIA). These DICOM format images are preprocessed, converted into PNG format, and normalized to ensure compatibility with deep learning workflows. Lesion regions are annotated using Makesense AI, generating YOLO-format label files for object detection training. Subsequently, Several YOLO versions model including YOLOv8, YOLOv5, YOLOv9, YOLOv10, YOLOv11, and YOLOv12 are trained and evaluated to identify the most effective architecture for lesion localization and classification.
The best-performing YOLO model, YOLOv11, is then enhanced with a hierarchical fuzzy inference system to refine predictions and manage uncertainties in lesion classification. Fuzzy membership functions are defined for each class Normal, Lytic, and Blastic and hierarchical fuzzy rules are applied to optimize the final decision-making process. The complete framework is implemented in the Google Colab environment using Python and deep learning libraries such as OpenCV and PyTorch. This standard metrics will be established to analyze model performance against confusion matrices, recall, and precision, F1-score, and accuracy, which will ensure clinical relevance and credibility of the suggested system.

1.5 Project Outcome

Improved Enhanced Accuracy in Lesion Detection: The integration of YOLO object detection with fuzzy logic layer is expected to improve the accuracy of identify and classify spinal lesions into Normal, Lytic, and Blastic classes. This framework minimizes the constraints relating to manual interpretation and wrong predictions.
Early Diagnosis and Faster Decision-Making: The proposed system can assist radiologists in detecting metastatic bone lesions at an early stage,enabling timely clinical interventions and minimizing the possibility of complications.
Evaluation of YOLO Models: Several versions of YOLO, such as YOLOv5 to YOLOv12, are tested on the criteria of the performance measures such as accuracy, precision, recall, F1-score, and confusion matrices to identify the most efficient architecture to use to detect and classify spinal lesions.
Development of a Hybrid Intelligent Framework: The framework combines YOLO and hierarchical level fuzzy logic to develop a smart diagnostic system to process the uncertainty in uncertain cases to enhance robustness as well as interpretability of the prediction.
Research Contribution and Innovation: This work is relevant in medical imaging AI development as it provides an indicator of hybrid YOLO-fuzzy logic systems effectiveness in cancer diagnosis. It has also provided a foundation of future extensions, such as to other cancer types or segmentation features or application of the system to clinical practice.

1.6 Organization of the Report

This thesis is structured in a manner that takes the reader through the research methodology, results of the experiment and the practical significance of the research under the title of; A Deep Learning Customizable Framework to Spine Metastatic bone cancer detection and classification depending on hierarchical fuzzy model. All the chapters are to be precise so the document should have clarity, continuity and logical flow.

Chapter 1: Introduction

This chapter explains the importance of early diagnosis in cases of spinal metastatic bone cancer and also talks about the weaknesses of the traditional diagnostic methods. It presents the research motivation, objectives, and the proposed solution a hybrid AI framework combining YOLO object detection with hierarchical fuzzy logic.This chapter also gives a brief overview of how the thesis is organized.

Chapter 2: Literature Review

This chapter reviews related works and existing methodologies in spinal lesion detection using machine learning and deep learning approaches. It examines studies involving YOLO-based detection, fuzzy classifiers, and hybrid models, while identifying research gaps that this study intends to overcome.

Chapter 3: Research Methodology

This chapter describes the complete workflow of the research, including dataset collection from TCIA, DICOM to JPG conversion, annotation using Makesense AI, and training of multiple YOLO models. It also elaborates the incorporation of hierarchical fuzzy logic in order to refine decisions, and evaluation strategies as well as performance metrics that will be used to measure effectiveness of the model.

Chapter 4: Implementation and Results

This chapter presents the implementation of the proposed system, including both qualitative and quantitative results. It provides a comparative analysis of different YOLO versions and demonstrates the performance improvements achieved through the integration of the hierarchical fuzzy inference layer. Measures used to evaluate accuracy, precision, recall, F1-score, and confusion matrices are some of the metrics used to evaluate.

Chapter 5: Engineering Standards and Design Challenges

This chapter explains the software and hardware requirements used in developing the system. It also covers engineering problems that have been met, ethical issues, the impact that the project has on society and the environment, project budgeting, financial planning and problem-solving solutions of complex problems that were employed throughout the research.

Chapter 6: Conclusion

The final chapter summarizes the findings of the study and evaluates the effectiveness of the proposed YOLO + hierarchical fuzzy logic framework. It states clinical application recommendations, the limitations that it experienced in the course of its research and the future work directions to enhance the model's scalability, accuracy and its implementation in real-world medical environments.

Chapter 2

Background

This chapter seeks to present a summary of the background knowledge one needs to be aware of when learning about the proposed study on spinal metastatic bone cancer detection with deep learning and fuzzy logic. It introduces key concepts such as the clinical relevance of spinal metastasis, existing diagnostic challenges, and the evolution of AI-based diagnostic systems.

2.1 Introduction

Bone metastatic spinal cancer is a very dangerous condition in patients with advanced malignant conditions which in most cases lead to immense pain, neurological impairments and reduced quality of life unless detected in time. Although standard or traditional methods of imaging like CT and MRI are necessary in diagnosis, manual analysis may be time consuming and may lead to human errors. The development of artificial intelligence in medicine has brought new deep learning models, especially YOLO used to detect objects in real-time, which demonstrated impressive possibilities to use machine learning in auto processing of medical images. However, these models can give dynamic results in unfamiliar or unclear scenarios. These algorithms can make diagnostic decisions more reliable, and interpretable by adding human-like reasoning to the classification procedure with hierarchical fuzzy logic. The current chapter gives the required background regarding the spinal metastasis and technological basis of the hybrid YOLO + fuzzy logic framework, which will undertake the spinal lesions in this paper, in order to achieve optimistic and precise identification of these lesions.

2.2 Literature Review

Aarthy et al. (2024) [1] presents a four-step deep learning framework that uses a Generative Deep Belief Neural Network (GDBN) to detect bone cancer. Their model divides bone tissue into three categories:, non-viable tumor, non-tumor and viable tumor. It combines Gated Convolutional Neural Networks (GCNN) for extracting features and applies preprocessing methods such as Maximally Stable Extremal Regions (MSER) to improve image region extraction. This study highlights how deep learning can boost the accuracy of bone cancer classification. However, it does not focus on model transparency or explainability, which are important for clinical trust. Moreover, the framework does not incorporate fuzzy logic, which could have helped make the decision process more interpretable.

Jeong et al. (2024) [3] created AI models to distinguish metastatic spine cancer from spinal compression fractures using MRI scans. They have used convolutional neural networks (CNN) and support vector machines (SVM) where they used preimages such as Otsu binarization and Canny edge detection. High sensitivity (1.00) and accuracy (0.98) with the CNN model on T1-weighted images showed the potential of AI-assisted diagnosis to improve clinical decision-making when it comes to identifying spinal conditions.

Imam et al. (2025) [4], the commonness and distribution of bone metastasis was established in cancers in Sudan by whole-body bone scan. They investigated 150 patients recruited at the Tumours Therapy and Cancer Research Center in Shendi, Sudan, and confirmed that 40 per cent had bone metastases. The main most frequent cancers which most frequently caused bone metastasis were breast cancer (35.3 in the left breast, and 20 in the right) and prostate cancer (22). The spine was the most involved site of the disease, the lumbar vertebra being involved in 51.7 and thoracic vertebra in 50.0%. The results highlight the significance of early diagnoses and specific treatments of bone metastases among the cancer victims.

Wang et al. (2024) [5] presented a machine learning solution to determine spinal bone mineral density (BMD) with high-resolution computer tomography (HRCT) images. Their process entails correct removal of the trabecular component of the vertebral bodies and as a result, the bone density is measured accurately. The aim of the technique is to provide more precise measurement of the spinal BMD to enhance the grading of osteoporosis, particularly in the elderly. The article represents potential of the combination of machine learning tools and HRCT imaging to advance the diagnosis and treatment of osteoporosis.

Zhang et al. (2023) [7] developed an artificial intelligence application that detects and forecasts spinal illness due to a combination of Synthetic Minority Oversampling Technique (SMOTE), Recursive Feature Elimination (RFE) and Extreme Gradient Boosting (XGBoost). This paper tackled the class imbalance issue of the dataset using SMOTE, RFE was used to pick suitable features, and it used XGBoost to classify. The accuracy of the model was 97.56, with F1-score of 0.8696, which showed the model to be effective in predicting spinal diseases. The other characteristics that influenced the model were lumbar slippage, cervical tilt, pelvic radius and pelvic tilt that highlight the importance of the two parameters in assessing the wellbeing of the spine.

Raihan-Al-Masud et al. (2020) [8] created a machine learning system to diagnose spinal anomalies on a dataset consisting of 310 samples. They applied the extraction of the features as by the univariate feature selection and the principal component analysis (PCA) and the classification with support vectors machines (SVM), logistic regression (LR) and bagging ensemble approach. The bagging SVM model had the greatest test-acquiring 86.96% and better recall and worse miss-rates. This paper highlights the value of integration of feature selection methods and ensemble learning.

Dunning et al. (2012) [10] discussed the difficulty in the management of metastatic spinal disease, which appears in 10%-30% of newly diagnosed cancer patients annually. The enhanced their coverage noted that treatment methods including surgery and radiotherapy aim at alleviating pain and maintaining functioning, but are more of a palliative nature. Surgical interventions are believed to be used in patients whose spinal instability or progressive neurological impairments and tumors that are resistant to radiotherapy. The procedures though are dangerous and their side effects such as bleeding, infection and even neurological complications exist. This article identifies the necessity of applying multidisciplinary approach in the efforts to ensure that patients achieve optimal outcomes when undergoing palliative care.

Abdullah et al. (2018) [9] trained a machine learning model to clearly identify spinal abnormalities in a dataset of 310 samples. The aim of the study was to extract features and executive classification algorithms to detect the spinal conditions accurately and correctly. The study attempted to increase the accuracy of diagnoses as well as aid clinical judgments during the identification of the spinal abnormalities by using the techniques of machine learning. The outcomes have indicated potentials in using machine learning in the field of medical diagnostics to improve the outcomes of patients.

Fan et al. (2021) [13] the researcher designed a deep learning neural network to detect the presence of spinal bone metastasis in patients with lung cancer with MRI images. The experiment used AdaBoost as the classification algorithm and the Chan-Vese algorithm as an image segmentator and evaluated the performance of this segmentation through the values such as the Dice index and the Jaccard coefficient. It was demonstrated that the model was highly efficient in the classification and division of the metastatic regions, which lays the future use of AI in enhancing the image-diagnostic positions of spinal metastases.

Buhmann et al. (2009) [11] carried out a research to find out the diagnostic accuracy on high-resolution multi-detector computed tomography (MDCT) versus magnetic resonance imaging (MRI) to detect vertebral metastases. A total of 639 vertebrae (of 41 patients who had various primary cancers with histological confirmation) participated in the research. It was found that, MRI was more sensitive (98.5) than MDCT (66.2) in detecting the metastatic lesions. However, both modalities had a similar specificity (MDCT: 99.3; MRI: 98.9%). These findings were: Despite its high spatial resolution and excellent image quality, MDCT is inferior to MRI in sensitivity to detect the presence of the osseous metastases especially when the bone is not severely involved.

Huang et al. (2025) [15] tested several variants of You Only Look Once (YOLO) model, namely, YOLOv5, YOLOv8, YOLOv9, YOLOv10, and YOLOv11, and assessed their performance in detecting and classifying lung cancer in CT images. The study showed that YOLOv8 performed the best, achieving a precision of 90.32% and a recall of 84.91%, highlighting its effectiveness in helping doctors diagnose lung cancer and accurately locate and identify the disease.

A summary of literature review provided in Table 2.1, highlighting the key features, methodology and finding of each study.

Table 2.1: Summary of Literature Reviewed.

Author	Year	Dataset	Methodology	Classification	Accuracy	Remarks
Aarthy et al. [1]	2024	1114 osteosarcoma images	GCNN + MSER	Binary	80%	Deep learning model, but lacks fuzzy logic and interpretability
Hossain et al. [2]	2018	120 MRI images	FCM + ANFIS	Binary	93.75%	Used fuzzy logic, interpretable model
Jeong et al. [3]	2024	248 spine MRI images	CNN + SVM	Binary	98.2%	High accuracy, no fuzzy logic
Imam et al. [4]	2025	150 patient bone scans	Statistical (no ML model)	Metastasis pattern only	Not applicable	Purely observational study, no classification model
Wang et al. [5]	2024	183 HRCT scans	ML on trabecular structure	Bone density analysis	Stable results	Focused on bone density, not cancer classification
Shrivastava et al [6]	2024	Not stated	SVM & RF with HOG	Binary	F1 = 0.92 (SVM)	SVM performed better; no fuzzy or deep learning used
Zhang et al. [7]	2023	310 spinal cases	SMOTE-RFE-XGBoost	Binary	97.56%	Utilized feature selection and oversampling to enhance spinal disease classification accuracy.
Raihan-Al-Masud et al [8]	2020	310 spinal cases (Kaggle)	Univariate Feature Selection, PCA, SVM, LR, Bagging	Binary	86.96%	Used feature selection and ensemble methods; Bagging SVM had the best recall and lowest miss rate.
Abdullah et al. [9]	2018	310 spinal cases	PCA, KNN, Random Forest	Binary	KNN: 85.32%, RF: 79.57%	Found spondylolisthesis degree most impactful; KNN outperformed RF in predicting spinal issues.

Dunning et al. [10]	2012	Not specified	Clinical review of metastatic spinal disease management	Not applicable	Not applicable	Emphasizes a multidisciplinary approach to metastatic spinal disease, focusing on palliative care, surgery, and radiotherapy.
Buhmann et al. [11]	2009	639 vertebral bodies from 41 patients	Comparative study of MDCT vs. MRI for detecting spinal metastases	Binary	MDCT: 88.8%, MRI: 98.7%	MRI demonstrated significantly higher sensitivity (98.5%) compared to MDCT (66.2%) in detecting vertebral metastases.
Uchida et al. [12]	2013	227 patients with suspected spinal metastases	Comparative study of 18F-FDG PET/CT vs. bone scintigraphy	Binary	PET/CT: 98.5% sensitivity; Bone Scintigraphy: 66.2% sensitivity	18F FDG PET demonstrated significantly high sensitivity in detect both osteolytic and osteosclerotic vertebral metastases compared to bone scintigraphy.
Fan et al. [13]	2021	MRI images from 87 patients with lung cancer spinal bone metastasis	AdaBoost algorithm and Chan-Vese (CV) segmentation	Binary (Metastasis vs. Non-metastasis)	Not specified	Used AdaBoost for classification and CV algorithm for segmenting images to detect spinal bone metastases in lung cancer patients.
Wang et al. [14]	2019	1,196 patients with spinal metastases	Retrospective epidemiological study	Not applicable	Not applicable	Outlined the epidemiology of spinal metastases in China, identifying lung cancer as the leading primary tumor and highlighting common issues like spinal cord injuries and patient pain.

H. Huang et al. [15]	2024	20,381 CT images on lung cancer	Comparat ive analysis on YOLO models	Four class used in this Paper	Precision 90.32% and Recall 84.91%	All YOLO versions were applied for lung cancer detection, and YOLOv8 gain the best results, but the Fuzzy model was not used.
Proposed Model	2025	Spine metastati c CT/MRI images	Deep Learning + Hierarchi cal Fuzzy Model	Multi-clas s (Normal, Lytic, Blastic)	93.69%	Combines DL + Fuzzy Logic + Feature Selection for accuracy and interpretability

Gap Analysis

Even though deep learning has significantly improved medical image analysis and cancer detection, current systems for spinal metastatic lesion detection and classification remain limited. Most studies either focus only on detection or only on classification, instead of combining both in a unified framework that can meet clinical needs. Although CNN-based methods are effective at identifying abnormalities, they can often fail to localize lesions accurately in multifaceted spinal CTs, and their black-box character diminishes clinical confidence because of interpretation deficits. Fuzzy logic, on the other hand, offers the ability to handle uncertainty and provide more explainable decisions, yet it is rarely integrated with deep learning models in this domain. Similarly, the YOLO family has shown great promise in fast and accurate detection tasks, especially in lung cancer imaging, but its application to spinal lesion detection is still scarce, and no work has explored its integration with hierarchical fuzzy logic. This creates a clear research gap for developing a hybrid model that combines YOLO's real-time detection capabilities with the interpretability of fuzzy reasoning to deliver a clinically reliable system that can both detect and classify spinal lesions (Normal, Lytic, and Blastic) in a transparent and trustworthy way.
Many studies have been conducted on medical images like spine lesion detection. But a careful comparison of existing works reveal the limitation and unexplored area. To highlight those limitations, a gap analysis table 2.2 given below.

Table 2.2: Gap Analysis Table

Features	Aarthy et al. [1]	Hossain & Rahaman [2]	Jeong et al. [3]	Shrivastava & Nag [6]	Raihan-Al-Masud & Mondal [8]	Proposed system
Lesion Localization (Object Detection)	No	No	Yes	No	No	Yes
Lesion Classification	Yes	Yes	Yes	Yes	Yes	Yes
Fuzzy Logic / Uncertainty Handling	No	Yes	No	No	No	Yes
YOLO Architecture Used	No	No	Yes	No	No	Yes
Detection & Classification Network	No	No	Yes	No	No	Yes
Cross Validation	No	Yes	No	No	No	No
Multi-Class Detection (Normal, Lytic, Blastic)	No	No	No	No	No	Yes

2.2 Summary

This chapter provided the essential background needed to understand the motivation and design of the proposed system for detecting spinal metastatic bone cancer. It demonstrated the clinical significance of the early diagnosis, potential strengths and weaknesses of the currently available imaging and AI-based tools were touched upon, and the importance of the deep learning and the fuzzy logic in analysis of medical images. There was also a concise gap analysis, which considered the study done in the recent interested literature and where the current systems are failing. In general, this chapter will form the basis of the hybrid framework based on detecting objects using the YOLO system and relying on the hierarchical use of the fuzzy logic hierarchy to provide a more accurate, reliable and interpretable diagnostic solution.

Chapter 3

Research Methodology

The chapter is a description of step by step procedure used in the creation of an intelligent system to detect and classify spinal metastatic bone lesions. The methodology consists of pre-processing, data collection, model-training, the introduction of the fuzzy logic and assessment. The key idea is to develop a powerful, faithful, and amiable diagnostic quantum of using YOLO to detect lesions and hierarchical fuzzy logic to extract the decisions.

3.1 Methodology

The objective of this study is to create an automated lesion-detecting and lesion characterizing system that classifies spinal CT lesions: the Normal, Lytic, and Blastic category. Prepared and annotated dataset was curated and preprocessed and subsequently divided into training, validation and test. YOLO models were trained to detect lesions, and fuzzy logic was added to it to handle uncertainties and improve more fine classification.

3.1.1 Overview

This research focuses on developing an effective and reliable hybrid deep learning framework for spine metastatic bone cancer detection. The process begins with collecting the dataset and processing all the data in which CT images are divided into three classes (Normal, Lytic, Blastic) and annotating all data in YOLO format, so models can learn the exact position of lesions. The annotated data is then split into training, validation and testing sets to ensure balanced learning. After that, I train and evaluate all the YOLO models. The YOLO based deep learning model was trained with optimized hyperparameters like batch size, epoch are tuned according to my dataset. I observed the result of all YOLO models and with the best model I integrate fuzzy logic for better accuracy. The Output of YOLO including, bounding box, class labels and confidence score helps refine using fuzzy logic systems which can handle uncertainty and improve decision making with better accuracy. After all those processes, the model Performance evaluated through key matrix like F1 score, precision, recall, ensures that the efficiency and reliability of my proposed model.

3.1.2 Proposed Methodology

The principal steps of the proposed approach for my case are data collection, data preprocessing, split of a dataset (70% training, 15% validation, and 15% testing), training of YOLO models, integration of fuzzy logic, and system assessment. Evaluation of performance on the model is done based on the metrics of the confusion matrix, Precision, recall, F1-score, and mean average precision (mAP). Figure 3.1 displays the complete work-flow.

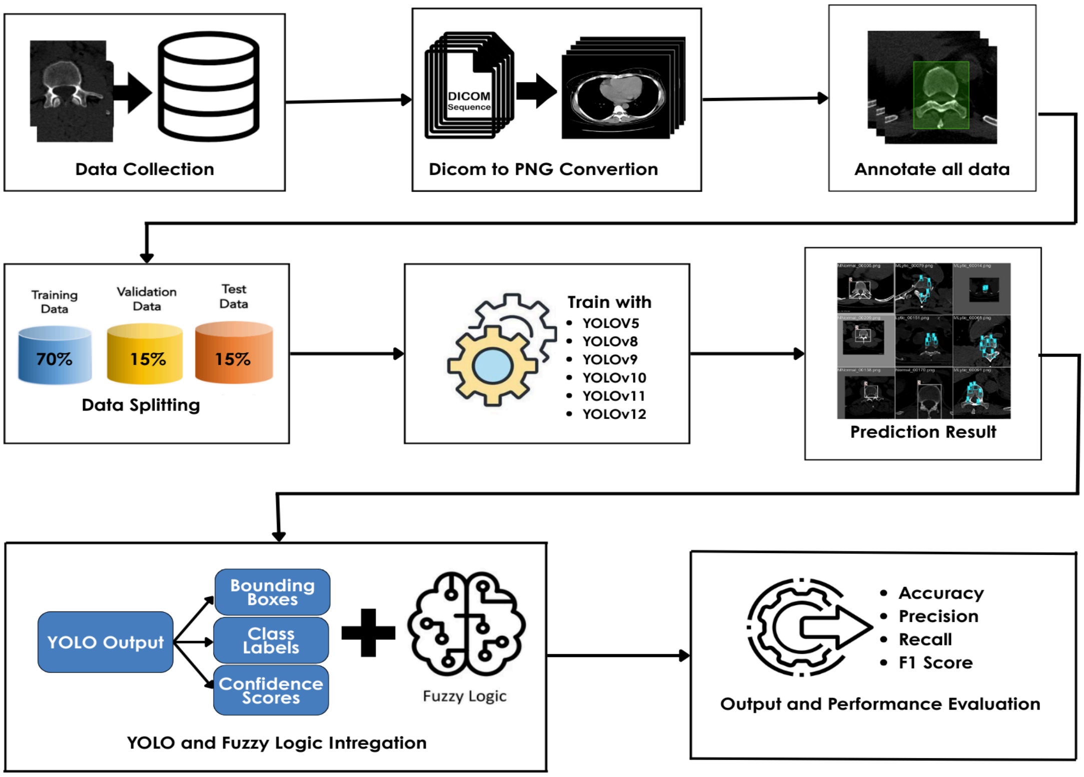
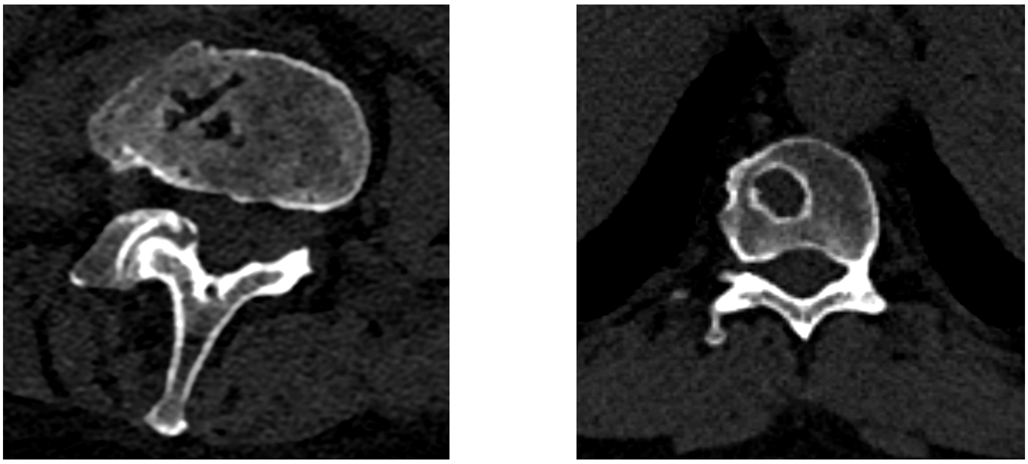


Figure 3.1: Process of Experiment

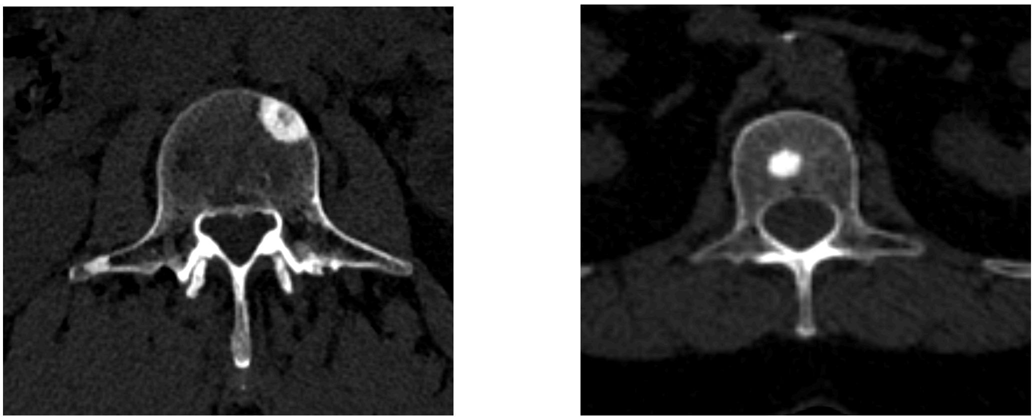
A. Data Collection

The dataset used in this study was obtained from The Cancer Imaging Archive (TCIA), specifically from the publicly available collection titled "Spine-Metastasis CT Segmentation". In the dataset, each image group Normal, Lytic and Blastic has its own subdirectory. There are 1367 PNG images available from the Normal, Lytic and Blastic categories. With my supervisor's assistance, I oversee my collection. These images are in DICOM format, a medical imaging standard format but I converted it into PNG format for easier processing. Three types of images shown in Figure 3.2.

A. Normal



B. Lytic

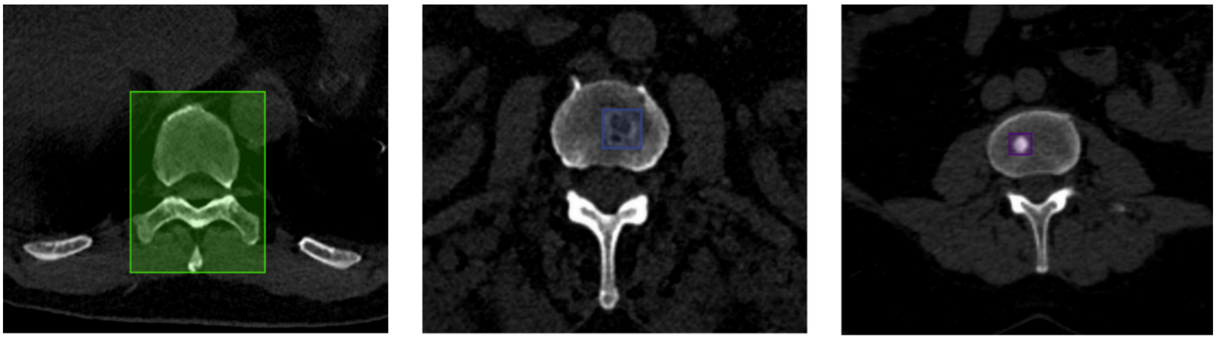


C. Blastic
Figure 3.2 : Few Images of Dataset

All the spinal CT scans in this study have been done as a routine in cancer diagnosis. Before using them in the research, each scan was carefully checked and make sure the spinal areas, especially the thoracic and lumbar vertebrae are clear and complete. The CT scans were scanned by two experienced radiologists who have then marked the scans as Normal, Lytic, or Blastic according to the medical guideline and this is mentioned in the dataset description. In case, any mistake occurred in their labeling, the case was examined by a third senior radiologist to make the final decision. This three- step checking process that guaranteed the image data was correct and reliable to train the model that made the detection and classification workflow more trustworthy.

B. Annotation

I annotated the CT images using Makesense AI. Lesion area in each image were manually annotated to create YOLO-format label files, including bounding box coordinates and class labels (Normal, Lytic, Blastic). Accurate annotation was critical for enabling YOLO models to learn accurate object detection and classification. Annotated images are shown in Figure 3.3.



Normal Lytic Blastic

Figure 3.3 : Annotated Images

After annotating the images, I divided the dataset into training, validation and testing. In Table 3.1, The detailed split ratios are presented.

Table 3.1: After Image Split

Set	Normal	Lytic	Blastic	Total
Train (70%)	301	355	299	956
Validation (15%)	64	76	64	205
Test (15%)	66	77	65	206

C. YOLO Models with Architecture

In this research, I trained and evaluated multiple YOLO models like YOLOv5, YOLOv9, YOLOv8, YOLOv10, YOLOv11 and YOLOv12. Each version has a different architecture. So, i give a short description with architecture about all those YOLO models below:

YOLOv5:

YOLOv5 runs on PyTorch and includes various size models to choose the balance between speed and accuracy. It presents a backbone with BottleNeckCSP feature extraction and a neck based on PANet (Path Aggregation Network) multi-scale feature fusion Which shown in Figure 3.4. The head uses anchor-based detection, and so, it is efficient in general medical imaging and less effective when a lesion is very small in CT scan.

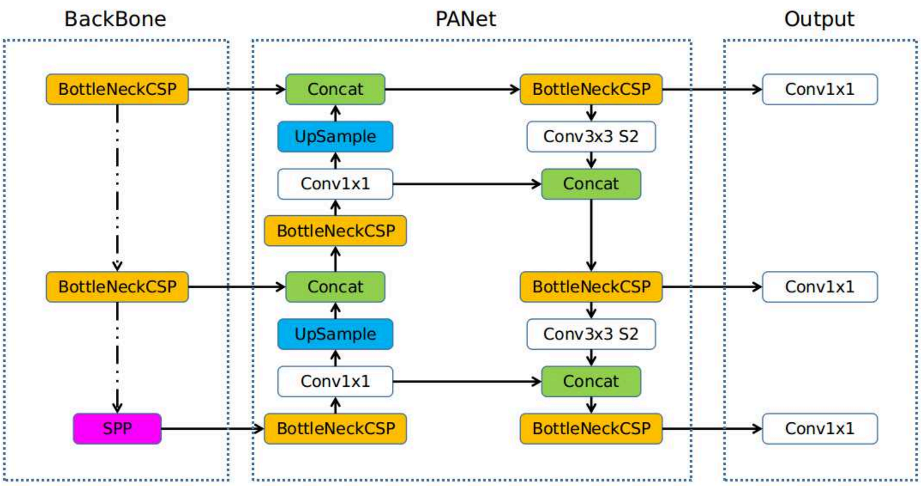


Figure 3.4: YOLOv5 Architecture

YOLOv8:

YOLOv8 has significant advances on YOLOv5, especially in accuracy and modularity. It optimizes backbone replacement with CSPDarknet with more versatile C2f (Cross Stage Partial with bottleneck expansion) architecture that enhances information circulation and feature representation. Its neck design offers better feature fusion that enhances small or complex abnormality detection in CT scan results. YOLOv8 is also more precise, recalls and robust than YOLOv5. This architecture illustrated in Figure 3.5.

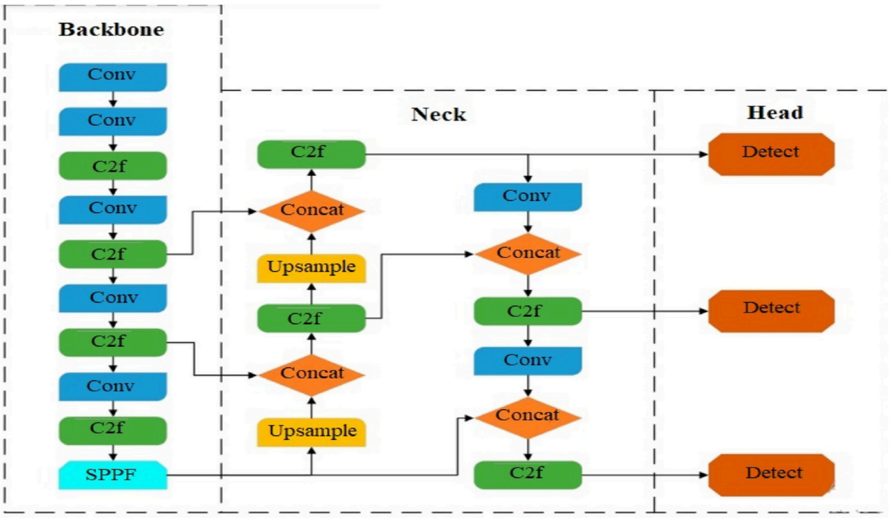


Figure 3.5: YOLOv8 Architecture

YOLOv9:

Figure 3.6 shows the architecture of YOLOv9 which presents an anchor free detection process to eliminate the use of manually defined anchor boxes. It consists of an advanced feature extraction backbone and effective attention-based modules. This architecture works very well with the subtle and overlapping lesions in CT scans. But it consumes more computational resources compared to YOLOv8.

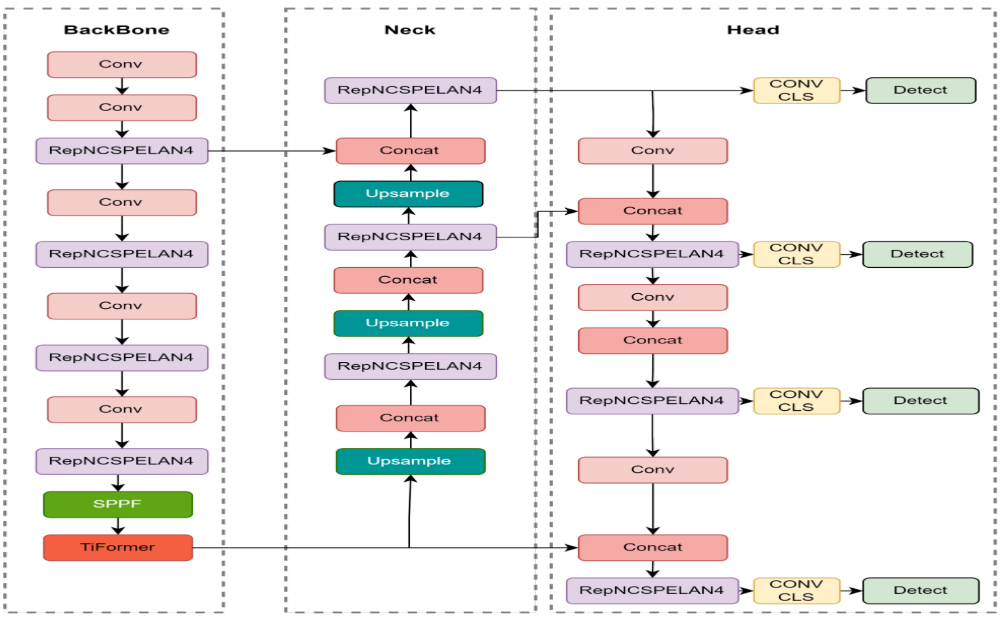


Figure 3.6: YOLOv9 Architecture

YOLOv10:

YOLOv10 is also about efficiency, and it tries to offer lightweight and fast inference without significant compromise in terms of accuracy. It has limited-resource optimization architecture and is feasible with large data collections.. Although not as accurate as YOLOv9 or YOLOv11, YOLOv10 is a highly efficient version since it can strike equilibrium between speed and reasonable accuracy. The architecture shows in Figure 3.7.

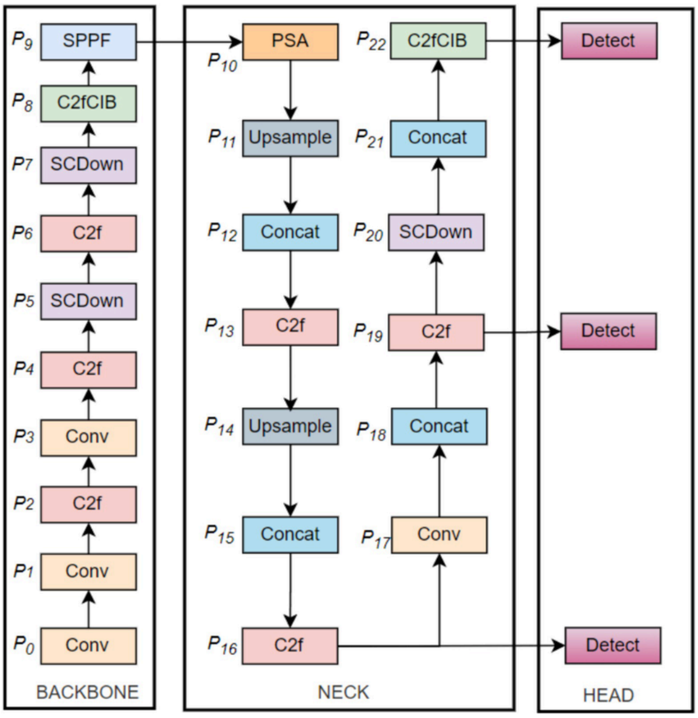


Figure 3.7: YOLOv10 Architecture

YOLOv11:

YOLOv11 is a stable and powerful pattern that produces high-level performance indicators in detection and classification matters. Architecturally, YOLOv11 is based on the anchor-free detect head proposed by YOLOv8 and YOLOv9 with extended optimization in its back bone and neck architecture. In the backbone, it employs a better C2f module, added with more residual connections, which enhances the propagation of features and also minimizes the loss of information in the feature during multiple layers. Its neck will associate PANet with further developed spatial pyramid pooling to capture more effectively the multi-scale lesion characteristics, which particularly can benefit medical images such as spinal CT scans where lesions can be of different sizes and shapes. All of these refinements increase precision, recall and F1-score, and are responsible for similar outputs. This characteristic of YOLOv11 contributes to producing the most suitable system that can be integrated with fuzzy logic where rating scales are needed as reliable detection confidence levels. Therefore, YOLOv11 is not overly focused on accuracy, robustness, and interpretability, which qualifies it as an effective candidate to be used in medical practice. YOLOv11 Architecture given in Figure 3.8.

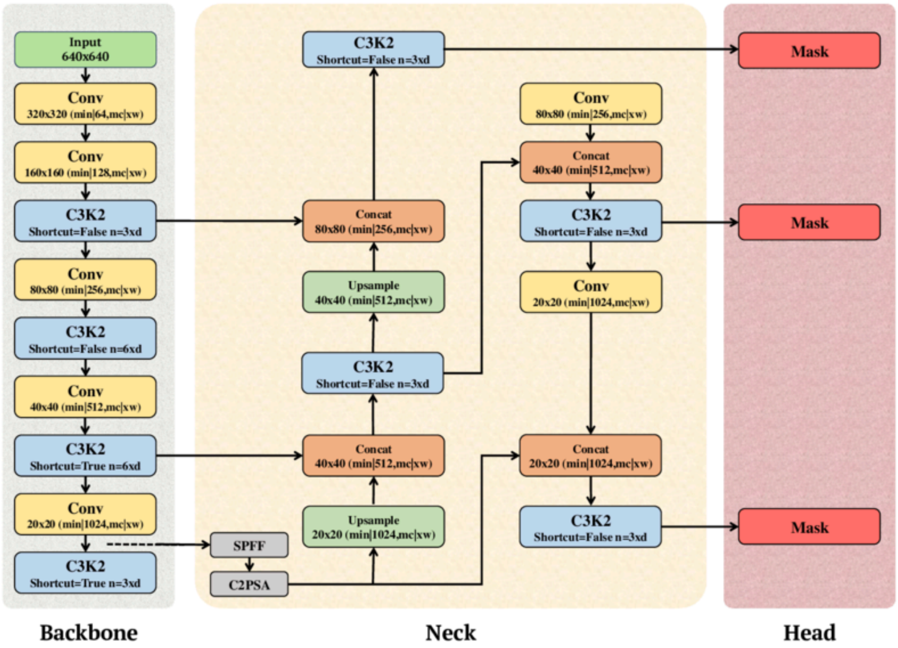


Figure 3.8: YOLOv11 Model Architecture

YOLOv12:

Figure 3.9 represents YOLOv12 which provides a re-developed backbone using dynamic receptive fields and BiFPN-esque feature fusion that improves fine-grained lesion localizations and multi-scale representation. It is the best in detecting small, overlapping defects with state of the art-accuracy. Nevertheless, its great computation cost and its heavier architectural design circumscribe its application to real-time, and it is more practical to its employment in research or precision-centered clinical applications.

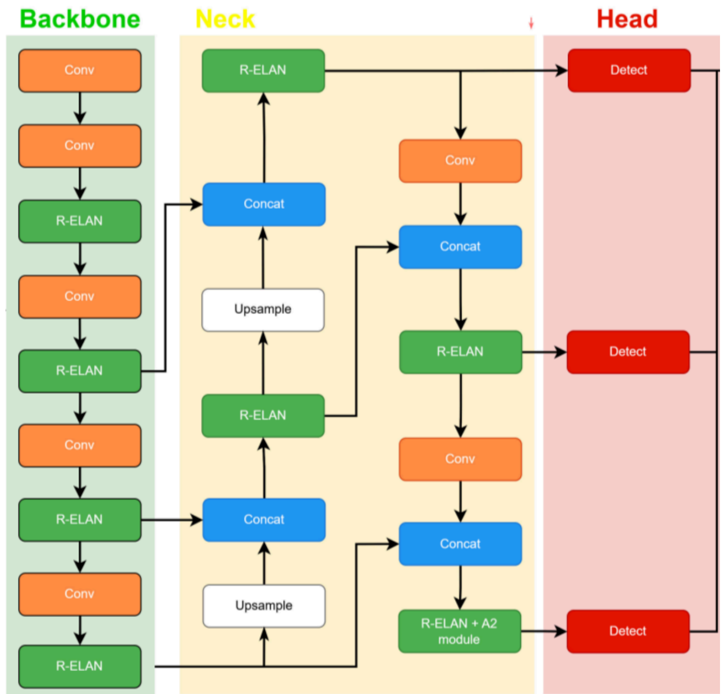


Figure 3.9: YOLOv12 Architecture

D. YOLO Model Training

In this stage represents training some YOLO versions, including YOLOv8, YOLOv5, YOLOv9, YOLOv10, YOLOv11, and YOLOv12, to evaluate their performance on the dataset. The hyperparameters were optimally trained, such as the batch size, learning rate, the number of epochs and size of images. The core loss can be viewed as analogous to objectness loss, classification loss, and bounding box regression loss to monitor their training efficiency. The dataset was divided into training, validation and test sets for balanced evaluation of each model's performance. The process of YOLO training illustrated in Figure 3.10.

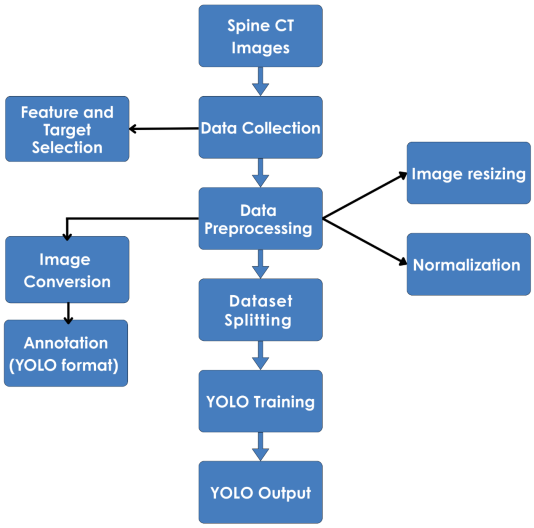


Figure 3.10: YOLO Training Process Block Diagram

E. Model Selection

After training all the YOLO versions, model selection was performed by comparing the YOLO versions based on mAP, precision, recall, and F1-score. YOLOv11 achieved best accuracy between all the models, illustrating better precision, recall, and training stability. Due to these characteristics, YOLOv11 was chosen as the baseline model for further refinement using fuzzy logic.

F. Fuzzy Logic Integration

Fuzzy Model :

Objective: To handle uncertainty and make human-like flexible decisions by using soft boundaries instead of strict classifications. The diagram of the fuzzy model shows in Figure 3.11. And Figure 3.12 demonstrated how the fuzzy logic works on the YOLO model. The process of fuzzy model given below:

Input from YOLO: After evaluation of YOLO model. The model provides Confidence score, bounding box and class labels.

Fuzzification: Those numeric values are converted into fuzzy sets like low, medium, high.

Rule Base: A set of "If–Then" rules is applied to the fuzzy inputs. Those rules are:

- If the Lytic probability is high While the Blastic probability is not high, classify the lesion as Lytic.
- If the Blastic probability is high while the Lytic probability is not high, the lesion is classified as Blastic.
- If Normal probability is high and the other two are low, classify as Normal.
- In case of conflict (if Lytic and Blastic probabilities are both medium), the system applies priority rules based on lesion area or box counts.

Inference Engine: The rules and membership are processed and then combined to make a decision.

Defuzzification: Transforms the fuzzy decision into either a final decision (Normal, Lytic or Blastic).

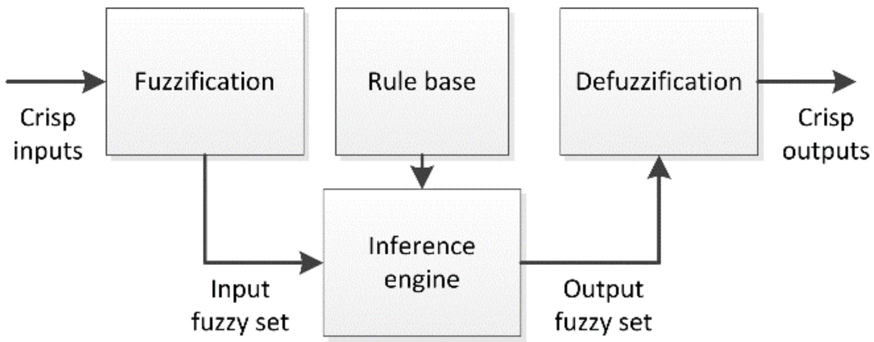


Figure 3.11: Fuzzy Logic Diagram

To handle uncertainty and improve accuracy, a hierarchical fuzzy inference system was integrated on YOLOv11. Confidence scores from YOLOv11 were as a input to fuzzy sets corresponding to the three classes: Normal, Lytic, and Blastic. Then hierarchical fuzzy rules applied to refine classification outputs, especially for images with overlapping lesions or low-quality scans. This fuzzy logic layer improved the reliability of the decisions and reduce the misclassification of uncertain cases.

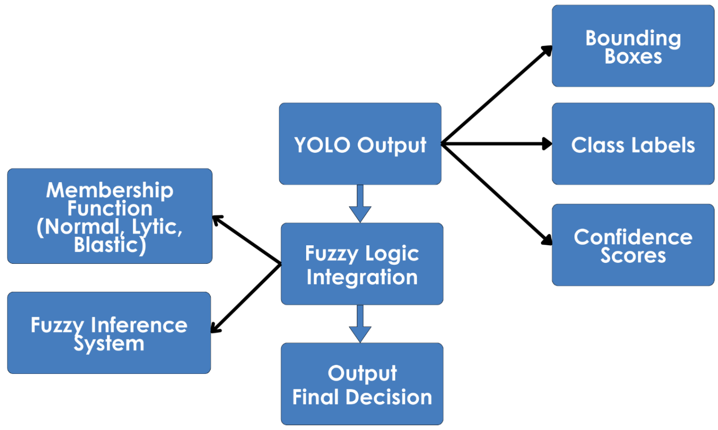


Figure 3.12 : Fuzzy Logic Decision Flow

3.1.3 Data Flow Diagram

A Data Flow Diagram (DFD) is added to further explain how the proposed system is working. The Figure 3.13 presents the flow of the input spinal CT image under various processes, which begin with the preprocessing and YOLO detections, which is further processed through fuzzy logic to produce the final output classes (Normal, Lytic, Blastic). DFD is useful to get a clear idea about how data flows as well as how various components of the system interact.

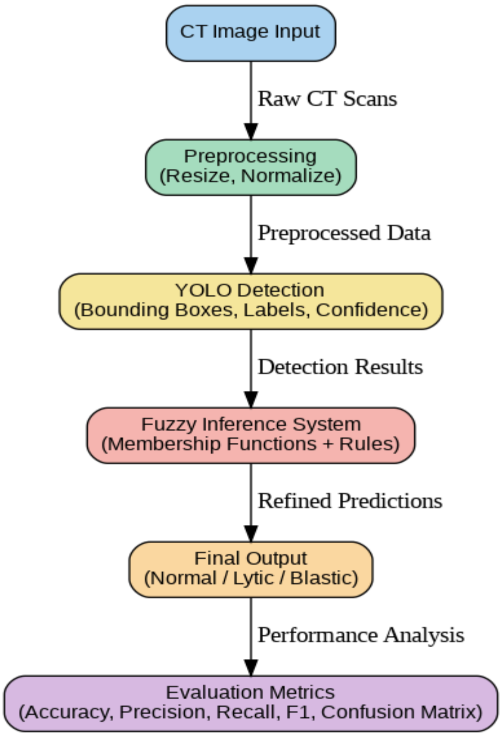


Figure 3.13: Data Flow Diagram

3.2 Detailed Methodology and Design

During the design phase, several approaches were evaluated:

1. CNN-only Classification
A pure convolutional neural network could classify spinal lesions directly from CT images.
Limitation: CNNs lack precise localization capability and cannot provide bounding boxes for lesions. They also have difficulties with ambiguous or overlapping cases, which have limited interpretability.

2. Object Detection Only (YOLO without Fuzzy Logic)
Using YOLO models alone allows lesion detection with bounding boxes and class predictions.
Limitation: YOLO predictions may be uncertain for borderline lesions or low-quality images, which could reduce reliability in clinical settings.

3. Traditional Machine Learning (SVM, Random Forest)
Feature-based classification using handcrafted features extracted from images.

Limitation: Performance heavily depends on feature selection, Which method takes more time and performs worse than deep learning on complex image patterns.

4.Ensemble Models

Using several models together for detection and classification to enhance performance.

Limitation: High computational cost and longer training time; still may not handle uncertain cases effectively.

3.3 Project Plan

Phase 1 – Problem Identification and Literature Review

- Identified the research gap in spine metastatic bone cancer detection.
- Conducted an in-depth literature survey on deep learning models (YOLO family) and fuzzy logic systems.
- Defined project scope, objectives, and expected outcomes.

Phase 2 – Dataset Collection and Preprocessing

- Collected CT scan images and organized them into three categories: Normal, Lytic, and Blastic.
- Performed preprocessing tasks such as resizing, normalization, and annotation (YOLO format).
- Separate the dataset into training, validation, and testing subsets to allow fair and unbiased assessment.

Phase 3 – Model Selection and Implementation

- Various YOLO versions (v5, v8, v9, v10, v11, v12) were implemented using Python and PyTorch.
- Compared performances based on accuracy, precision, recall, and mAP.
- Integrated a Fuzzy Inference System to enhance interpretability of classification outputs.

Phase 4 – Training and Evaluation

- Trained the models using annotated datasets with proper hyperparameter tuning.
- Used callbacks like early stopping and learning rate adjustment to enhance model performance.
- Evaluated models through confusion matrices, performance metrics, and visual outputs.

Phase 5 – Result Analysis and Optimization

- Compared YOLO-only results with the YOLO + Fuzzy hybrid approach.
- Selected the YOLOv11 + Fuzzy model as the best-performing framework.
- Conducted detailed analysis to highlight improvements in both accuracy and

explainability.

Phase 6 – Documentation and Reporting

- Compiled findings into a structured thesis report.
- Developed graphical models like charts, confusion matrices, and graphs to facilitate clarity.
- Developed a sustainability and future work plan to extend the research further.

3.4 Task Allocation

Table 3.2 shows the timeline of work in my research. It explains when data collection, preprocessing, YOLO training, fuzzy logic integration, testing, and documentation are done within those weeks.

Table 3.2: Task Allocation

Tasks	**Weeks**																		
	12	14	16	18	20	22	24	26	28	30	32	34	36	38	40	42	44	46	48
Data collection phase																			
Preprocess all the data																			
YOLO Model Training																			
Fuzzy Logic Integration																			
System Testing & Validation																			
Documentation																			

3.5 Summary

The implementation of the research titled "A Deep Learning Customized Framework for Spine Metastatic Bone Cancer Detection and Classification Based on Hierarchical Fuzzy Model" involves both technical and functional requirements to ensure a successful system design. The framework relies on multiple YOLO models (YOLOv5–YOLOv12) for accurate detection and classification of spinal lesions. YOLO has shown remarkable performance in medical image localization due to its real-time detection capability and high precision. To further enhance reliability, a hierarchical fuzzy logic layer is integrated with the best-performing YOLO model (YOLOv11) to address uncertainty in overlapping lesion features and to provide interpretable, human-like decision-making.

A set of 1,367 spinal CT scan images provided by The Cancer Imaging Archive (TCIA) has been curated and used as the proposed methodology. These original DICOM images have been changed to be in the form of PNG and annotated in an YOLO format with the help of the Makesense AI. The data were standardized by preprocessing including the steps like resizing and normalization. An annotated dataset was split into practice, validation, and test datasets that contained an equal chance to deliver an unbiased and correct assessment. Several variants of the YOLO algorithm were trained and assessed, and the most successful of them were improved using fuzzy logic. The Fuzzy Inference layer produces the optimal case to reject the misclassification in ambiguous cases by membership functions and hierarchical rules based on maximizing the YOLO confidence scores.

Key metrics to evaluate the effectiveness of a framework were accuracy, precision, recall, F1-score and confusion matrices, which ensured that it is trustworthy and relevant in clinical usage. Analysis of training and validation curves was also done to make certain convergence and consistency in the training process.

The software and hardware were to be seriously planned in the research. Model training and parallelized computation could only be done on machines with large models and paradoxically with the powerful CPU and ample RAM that would facilitate easy data processing. Python was used as the major programming language with PyTorch as the major deep learning platform to implement YOLO. Experimentation was done with additional tools like Google Colab and local development environments, whereas SSDs were used to assure the rapid loading of data and HDDs were used to store data in the long term.

The entire project flow involved the process of collecting the dataset, pre-processing, annotation, training of the YOLO model and introducing fuzzy logic, performance analysis, and project validation in the end. Intelligent interpretation with deep learning and the use of fuzzy logic within the proposed framework has provided a powerful diagnostic tool to detect and classify spinal metastatic bone cancer with greater precision, better interpretability and applicability in the practical world.

Chapter 4

Implementation and Results

This chapter shows how the provided framework is implemented and how it performs. It begins with the environment setup, which includes the description of hardware and software resources that should be used, continues with the preparation of the datasets and the model training, the fusion between fuzzy logic and the interpretation of results.

4.1 Environment Setup

To execute the suggested framework, both hardware and software materials, which were optimized towards deep learning experimentation, were needed. Medical image datasets are large and require a lot of computations, which makes it crucial to use systems with GPU acceleration to help minimize training and effective performance.

The research used was mainly done on Google Colab Pro that offers access to NVIDIA Tesla T4 and A100 GPUs. These GPUs allowed parallel training, minimized computing time and provided large scale processing of CT scan images. Moreover, preprocessing and dataset organization, as well as limited-scale testing, were performed with a local computer with a high-performance CPU and 16 GB of RAM.

In software, Python was chosen as the main programming language because of its adaptability and high level of support with scientific computation. Yolo model training and inference were trained using the PyTorch deep learning framework, and libraries like open CV, NumPy, and Matplotlib were utilized to process images, handle data, and visualize. Makesense AI was used to annotate the dataset enabling the generation of YOLO-compatible bounding boxes and class label text files.

To store data and manage datasets, Google Drive was integrated with Colab, which allowed transferring data easily and storing it without any issues. Solid-State drives were chosen as faster in loading the data when training a model and Hard Disk drives were applicable in datasets maintenance and backup.

Overall, the design had to be performance scalable at low cost, meaning that the structure could be designed and tested efficiently, despite real constraints in the world.

4.2 Testing and Evaluation/Performance/ Comparative Analysis

The evaluation of model performance was carried out using the following metrics:

- **Intersection over Union (IoU):** Measures the overlap between predicted bounding boxes and ground truth.

$$IoU = \frac{AreaofOverlap}{AreaofUnion} \tag{1}$$

- **Precision:** The percentage of predicted lesions that matched the actual lesions.

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

- **Recall:** The proportion of actual lesions that were correctly identified.

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

- **F1-Score:** Precision and Recall - Harmonic mean of Precision and Recall, which is a general measure of detection.

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (4)$$

- **Mean Average Precision (mAP):** Evaluates how accurate the model is across various IoU thresholds.. mAP50 shows the average precision when IoU = 0.50, while mAP50-95 calculates the average precision across IoU values from 0.50 to 0.95 in 5% steps, capturing both detection and classification quality.

Here, TP represents correctly detected lesions, FP represents falsely detected lesions, and FN represents missed lesions. By analyzing these metrics, the evaluation framework provides a comprehensive assessment of YOLOv11's performance for spine cancer detection and demonstrates the improvement achieved when integrating fuzzy logic for enhanced classification reliability.

Performance Evaluation

The performance of the proposed system was rigorously evaluated using multiple YOLO versions, including YOLOv5, YOLOv8, YOLOv9, YOLOv10, YOLOv11, and YOLOv12. Model parameters are shown in Table 4.1. Both training and test datasets were used to assess the models capabilities in detecting and classifying spinal metastatic bone lesions. The evaluation metrics included Box Loss, CLS Loss, DFL Loss, mAP@50, mAP@50–95, Precision, Recall, and confusion matrices, complemented by training and validation curves to analyze model convergence, learning stability, and generalization. The purpose of this thorough analysis was to find the most successful YOLO version that they would incorporate into the proposed hybrid model that would have hierarchical fuzzy logic.

Box Loss represents the model's ability to localize lesions accurately. A lower Box Loss indicates higher precision in predicting bounding box coordinates for spinal lesions.

TABLE 4.1: Model parameter settings.

Parameters	Values
Epochs	100
Image Size	640
Batch Size	16
Optimizer	Adam
Pretrained	True

For the training dataset, YOLOv11 achieved the lowest Box Loss 1.264, On the other hand, In test dataset the Box Loss 1.450, demonstrating its superior capability in learning lesion localization from the training data. YOLOv8 and YOLOv9 performed closely at 1.472, indicating effective learning but slightly lower precision. YOLOv12 recorded the highest Box Loss 0.898 and 1.41 in the validation dataset, suggesting suboptimal localization and learning stability.

On the validation dataset, YOLOv11 again maintained the best performance with Box Loss 1.450, confirming its strong generalization to unseen images. YOLOv8 followed 1.484, and YOLOv12 showed moderate performance 1.416. YOLOv10 exhibited the highest validation Box Loss 2.813, indicating difficulty in accurately localizing lesions outside the training set.

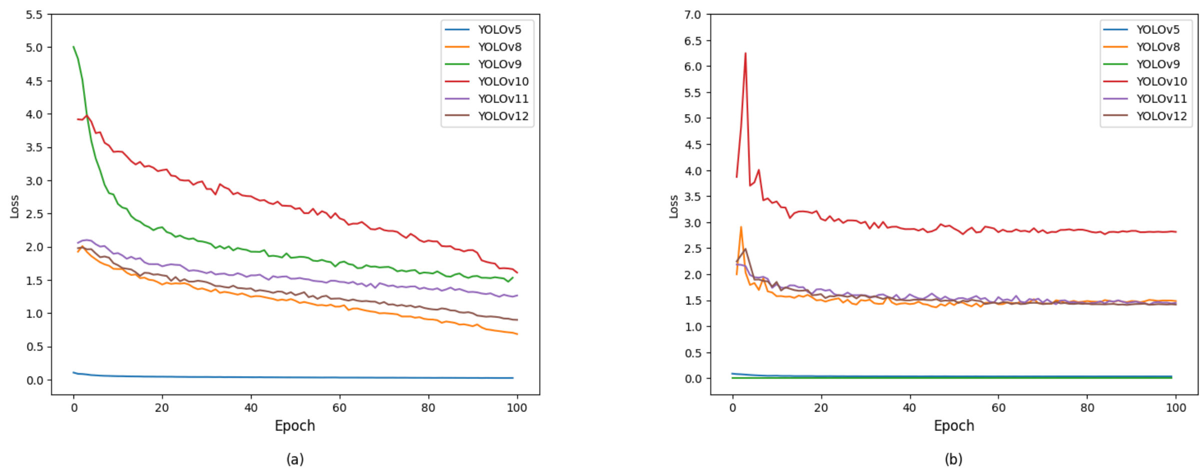


Figure 4.1: Box loss each model. (a) For training dataset. (b) For validation dataset

CLS Loss measures the accuracy of predicted lesion classes (Normal, Lytic, Blastic). Lower CLS Loss reflects better classification performance.

In the training dataset, YOLOv11 achieved the lowest CLS Loss 0.825, On the other hand test dataset Loss is 0.847 suggesting it learned discriminative features effectively. YOLOv8 followed closely 0.352 which is a good performance but in the validation dataset the difference has occurred overfitting, the CLS Loss is 0.822 whereas YOLOv12 had the highest CLS Loss 0.486, reflecting challenges in class separation for the validation dataset, YOLOv11 maintained best performance, highlighting robustness and generalization. YOLOv8 performed well, while YOLOv12 showed significant misclassification tendencies 0.808. Figure 4.2a illustrates CLS Loss for the training dataset and Figure 4.2b presents CLS Loss for the validation dataset.

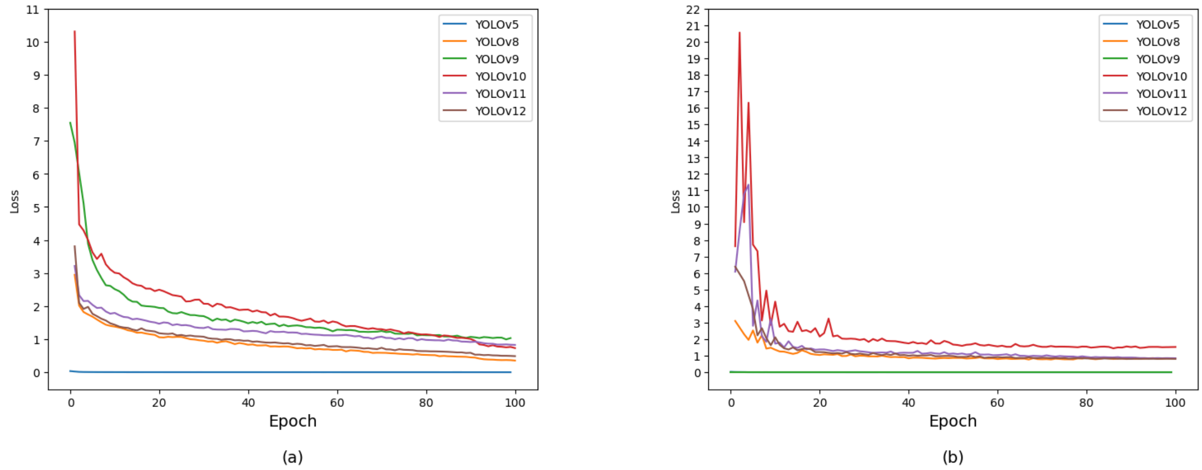


Figure 4.2: CLS loss each model. (a) For training dataset. (b) For validation dataset

DFL Loss reflects the model's confidence in object detection and the quality of focal predictions. Lower DFL Loss suggests more reliable detection confidence and fewer false positives

YOLOv11 achieved the best DFL Loss on the training dataset 1.263, followed by YOLOv9 is 1.509, indicating accurate confidence calibration. YOLOv12 showed the highest DFL Loss 1.034, which is not bad performance for DFL Loss. On the test dataset, YOLOv11 again performed the best 1.270, demonstrating robustness on unseen data. YOLOv8 and YOLOv9 had slightly higher values of 1.553, while YOLOv12 performed well followed by 1.380. Figure 4.3a illustrates DFL Loss for the training dataset and Figure 4.3b presents DFL Loss for the validation dataset.

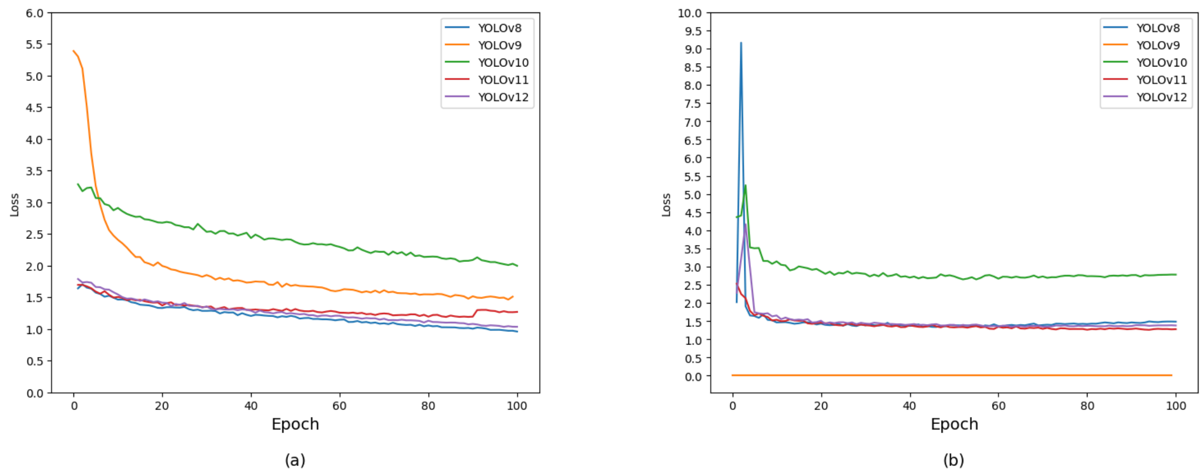


Figure 4.3: DFL loss each model. (a) For training dataset. (b) For validation dataset

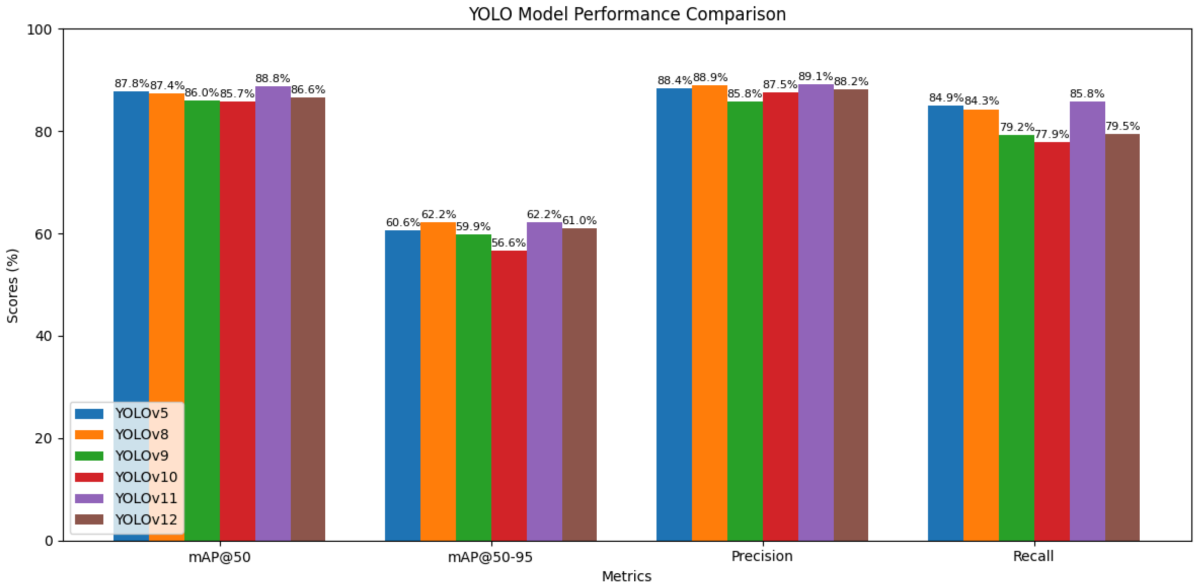


Figure 4.4: Model Effectiveness Evaluation

A comparative evaluation was conducted using multiple YOLO versions (YOLOv5–YOLOv12) to assess the performance of the proposed system on the spine cancer dataset. The comparison was based on four key performance metrics: mAP@50, mAP@50–95, Precision, and Recall. The results are summarized in Table 4.2.

From the results, it is evident that YOLOv11 achieved the highest overall performance, obtaining an mAP@50 of 88.8% and Precision of 89.1%, which are superior compared to other YOLO versions. In terms of Recall, YOLOv11 also performed better (85.8%), slightly outperforming YOLOv5 (84.9%) and YOLOv8 (84.3%). On the other hand, YOLOv5 and YOLOv8 delivered competitive performance with mAP@50 values of 87.8% and 87.4%, respectively, indicating that they are still effective alternatives.

Meanwhile, YOLOv9, YOLOv10, and YOLOv12 exhibited relatively lower performance, with Recall values ranging between 77.9% and 79.5%. Their mAP@50–95 values (59.9%, 56.6%, and 61.0%) were also lower compared to YOLOv8 and YOLOv11, highlighting reduced generalization capability in multi-IoU thresholds.

Table 4.2: Performance of the Model versions

Model	mAP50	mAP50-95	Precision	Recall
YOLOv5	87.8	60.6	88.4	84.9
YOLOv8	87.4	62.2	88.9	84.3
YOLOv9	86	59.9	85.8	79.2
YOLOv10	85.7	56.6	87.5	77.9
YOLOv11	88.8	62.2	89.1	85.8
YOLOv12	86.6	61.0	88.2	79.5

Confusion Matrix (All Model)

The confusion matrix illustrates how well the model performs and shows the detected number of lesions for each class. It displays the performance of the Normal, Lytic- and Blastic lesions and a background section that indicates part of the CT scans where no lesions had occurred. The Background helps to evaluate how well the model performs on true lesions from non-lesion regions, ensuring reliable detection. So, the difference of each model is given below.

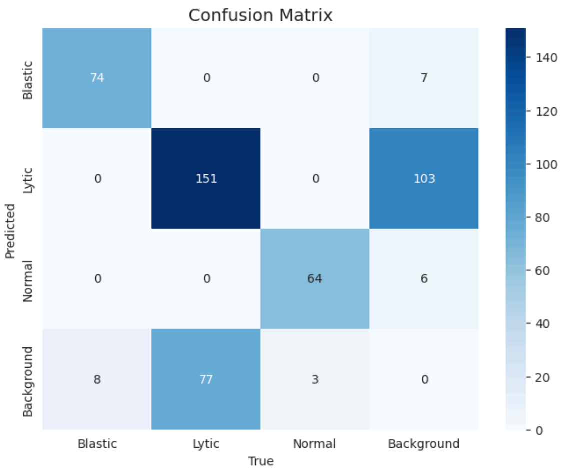


Figure 4.5: YOLOv5 Confusion Matrix

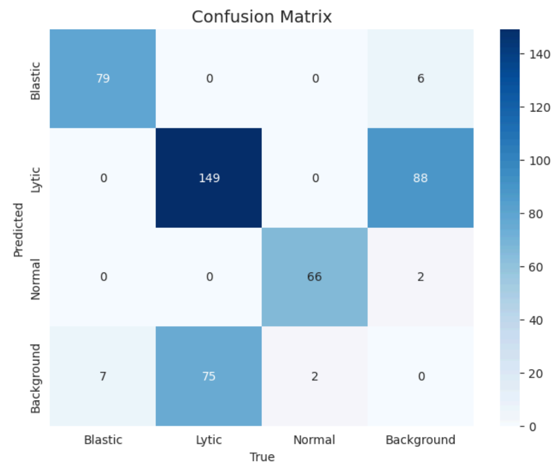


Figure 4.6: YOLOv8 Confusion Matrix

In Figure 4.5, YOLOv5 performed well in blastic and normal detection but a large number of misclassifications in lytic and background. On the other hand, YOLOv8 performs better than YOLOv5 but lytic remind of the major misclassification. The background and lytic class affect the overall accuracy.

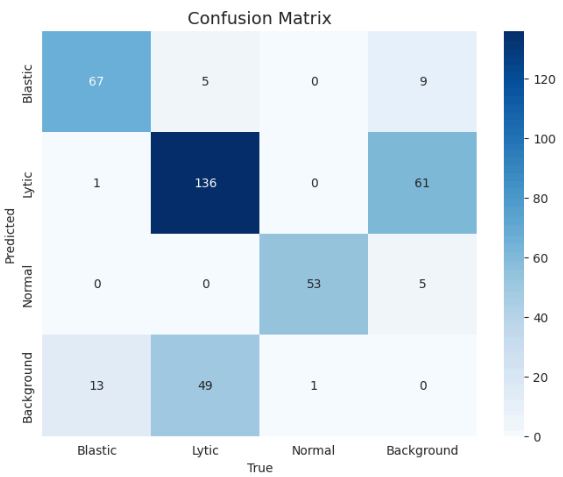


Figure 4.7: YOLOv9 Confusion Matrix

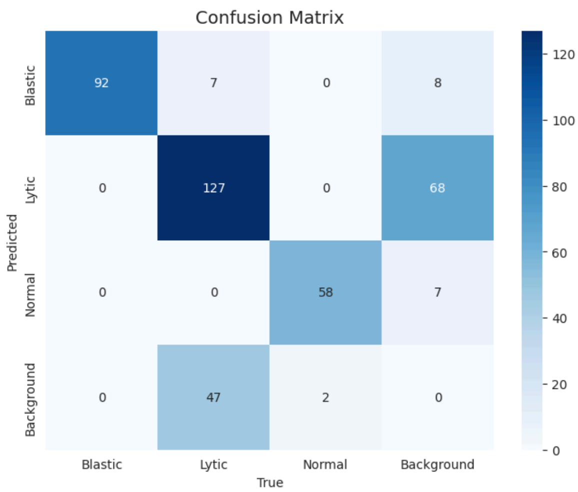


Figure 4.8: YOLOv10 Confusion Matrix

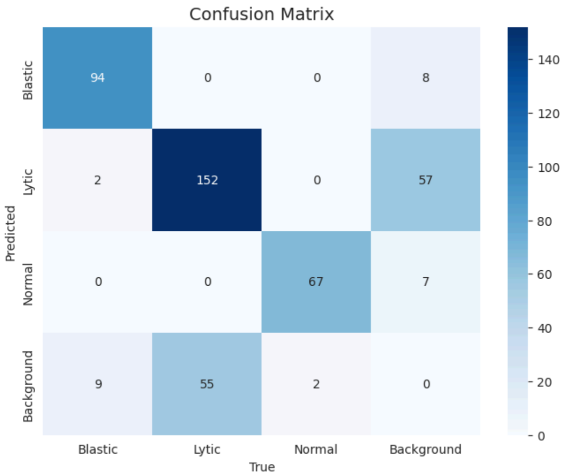


Figure 4.9: YOLOv11 Confusion Matrix

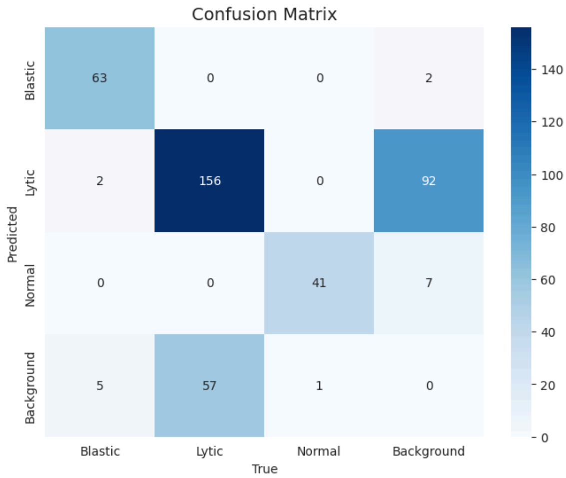


Figure 4.10: YOLOv12 Confusion Matrix

Based on those confusion matrix figures, YOLv9 shows average performance on Lytic and Blastic lesions but problems with Normal detection and background misclassification, thats why reduce overall accuracy. In Figure 4.8, YOLOv10 achieves the best Blastic detection but still suffers from high Lytic–Background confusion. YOLOv12 also performs well but performs poorly in blastic and normal classes. We can see in Figure 4.9, YOLOv11 performs better than others models. It is the most balanced performance between those models.

Comparative Analysis and Model Selection

A comprehensive comparative analysis was conducted across all YOLO versions (YOLOv5 to YOLOv12) to evaluate their performance on spinal metastatic bone lesion detection and classification. The comparison considered both loss metrics (Box Loss, CLS Loss, DFL Loss) and detection metrics (mAP@50, mAP@50–95, Precision, Recall, and F1-score) on training and test datasets. Box Loss evaluates how accurately the model pinpoints the location of lesions. Across the models, YOLOv11 consistently achieved the lowest Box Loss on both training and test datasets, demonstrating precise localization capability. YOLOv8 and YOLOv9 followed closely, indicating strong performance, while YOLOv10 and YOLOv12 showed higher Box Loss, reflecting less accurate localization and possible challenges in learning from the dataset. CLS Loss indicates how well the model classifies lesions as Normal, Lytic, or Blastic. YOLOv11 achieved the lowest CLS Loss, suggesting effective learning of discriminative features and superior classification performance. YOLOv8 also performed well with slight overfitting as seen in a slight rise in CLS Loss on the validation set. YOLOv12 presented the best CLS Loss, since it provides challenges in separating the classes correctly. DFL Loss assures the model of its confidence and reliability to detect objects. YOLOv11 showed the best results, making the lowest loss under any DFL, indicating less confidence, and reducing the chance of false positives. YOLOv8 and YOLOv9 had a higher DFL Loss but with YOLOv12, the predictions were moderately reliable.

In metrics of detection, YOLOv11 scored the highest mAP 50 88.8% and Precision 89.1% and a good Recall 85.8% indicating strong values in terms of balance between detection and classification. YOLOv8 was able to demonstrate competitive nature, slightly disadvantaged by mAP and Recall. YOLOv9, YOLOv10, and YOLOv12 fared comparatively worse with worse at least the ability to generalize, probably as a result of overfitting, a lesser number of parameters, or architecture bias. To explain the superior performance of YOLOv11, I want to mention its modern network architecture, parameter setup, and better generalization of unobserved images. Conversely, a weaker performance of YOLOv10 and YOLOv12 might be related to not enough feature extraction, model fluctuation, or excessive overfitting on the learning data.

In short, the comparative analysis shows that YOLOv11 is the most successful model to detect bone lesions of the spine metastases. This choice guarantees the correct localization, quality classification, and good generalization, and it is a solid basis of integration with the fuzzy logic layer to increase the diagnostic interpretability and reliability. The predicted output of YOLOv11 is illustrated in Figure 4.11.

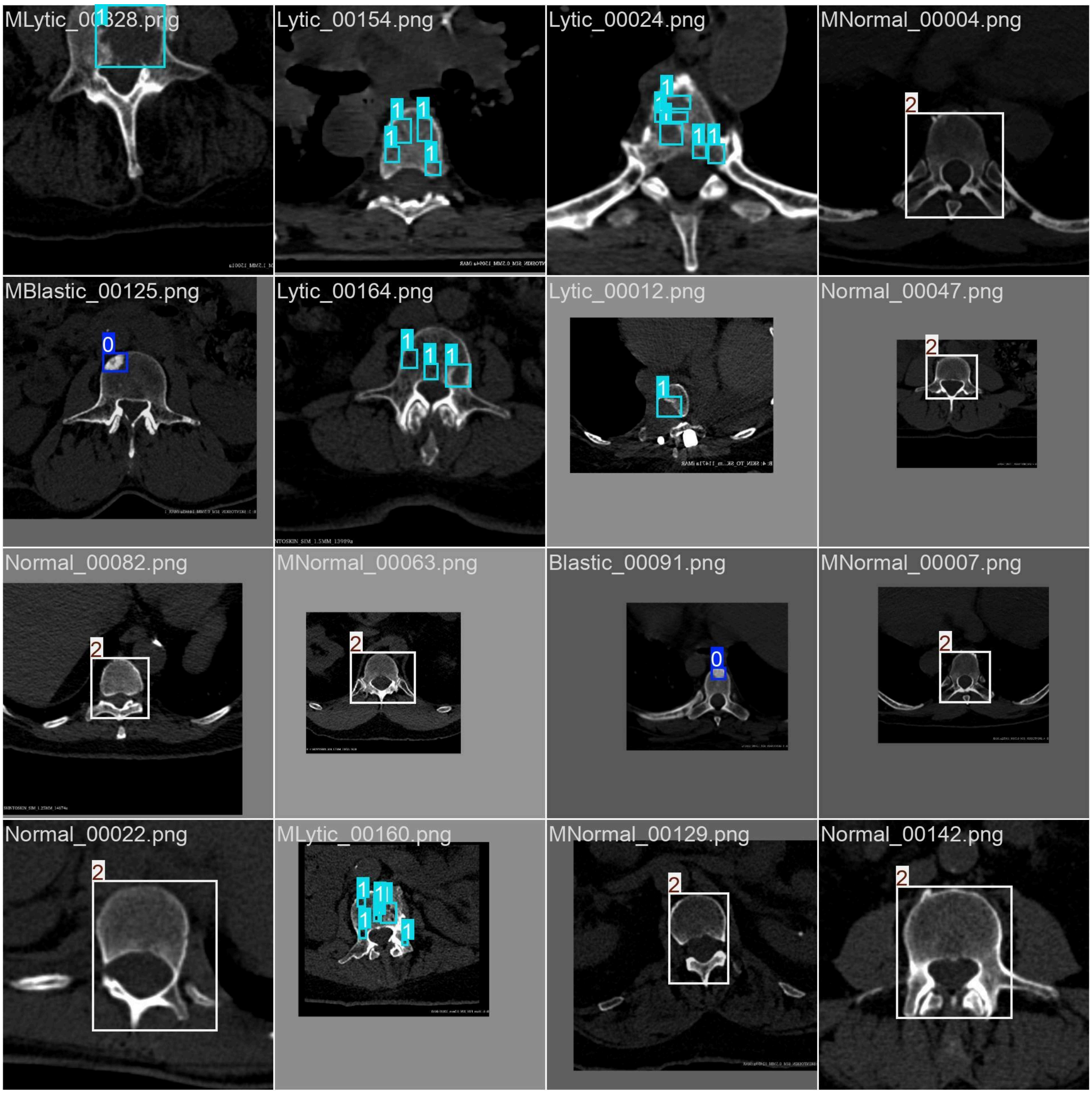


Figure 4.11: Prediction Result

Integration with Fuzzy Logic

In order to enhance the classification ability of the system based on YOLOv11 in detecting the spinal metastatic bone lesions, a fuzzy inferencing layer was added. YOLOv11 generates bounding boxes, class probabilities and confidence scores on each lesion detected. However, in some cases, predictions may be borderline or uncertain due to overlapping features, low contrast, or partial occlusion in the CT images. The fuzzy logic layer addresses these uncertainties by refining class predictions.

Performance Improvement

By combining YOLOv11 outputs with fuzzy logic, the system achieved an overall accuracy of 93.69%, improving over the original YOLOv11 performance. This integration proves:

Increased robustness: The system processes the ambiguous or borderline cases more effectively.

Better interpretability: Conclusions can be returned to particular fuzzy rules, which offer insight into borderline classification results.

Clinical applicability: The hybrid model makes the predictions more reliable which is a necessity in medical decision making.

FIgure 4.12 presents the confusion matrix after integrating YOLO with the Fuzzy model which results in better than YOLOv11.

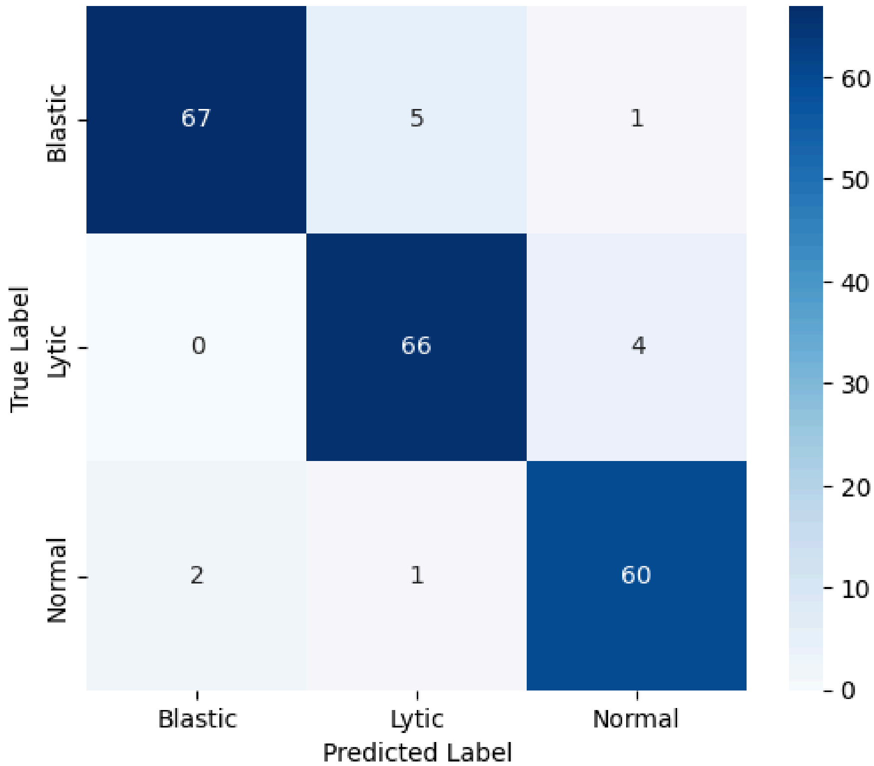


Figure 4.12: Confusion Matrix After Fuzzy Model

4.3 Results and Discussion

In order to validate the proposed framework, both YOLOv11 and the improved YOLOv11 + Fuzzy Logic pipeline were tested on the test dataset. Figure 1 demonstrates a visual comparison between the baseline YOLOv11 model and the fuzzy logic enhanced approach.

Table 4.3: YOLOv11 Performance

Model	Precision	Recall	mAP50	mAP50-95
YOLOv11	0.891	0.85	0.888	0.622

Table 4.4 : YOLOv11 integrate with Fuzzy Logic Performance

Class	Precision	Recall	F1-score	Support
Blastic	0.97	0.90	0.94	73
Lytic	0.90	0.94	0.92	70
Normal	0.92	0.95	0.94	63
Accuracy			0.93	206
Macro avg	0.93	0.93	0.93	206
Weighted avg	0.93	0.93	0.93	206

In this study, YOLOv5, YOLOv8, YOLOv9, YOLOv10, YOLOv11 and YOLOv12 were thoroughly compared and evaluated for detecting and classifying metastatic spine cancer using CT images. The experimental results indicate that YOLOv11 provides the most stable performance in terms of box regression loss, classification accuracy, and overall F1-score. However, when enhanced with a fuzzy logic decision layer, YOLOv11 reached a top overall accuracy of 93.69%, outperforming the other YOLO versions. This demonstrates the effectiveness of integrating fuzzy reasoning with deep learning for handling borderline cases in medical image classification.

The findings highlight the clinical value of the YOLOv11 + Fuzzy Logic hybrid framework, which provides a more robust and interpretable decision-making process. The model facilitates an early detection of metastatic lesions and how they can be addressed by classifying them into the following categories Normal, Lytic and Blastic. This ability has the potential to enhance the prognosis, facilitate the choice of therapy and eventually increase the survival rates of patients.

4.4 Summary

The proposed detecting and classifying metastatic spine cancer framework application was described in a process of its entire implementation in this chapter. Initial dataset preparation is next outlined, which involves an annotation, preprocessing and separation of the datasets into training enslaved subset, validation and testing enslaved subsets. A number of YOLO versions were trained and tested on a dataset with the same set of experimental conditions to facilitate a fair comparison.

The performance was evaluated with standard metrics of detection like mAP50, mAP50-95, precision, recall, and F1-score as well as loss values (box, class, and DFL losses). The results demonstrated that YOLOv11 achieved the most stable and accurate performance among all baseline models. To further enhance decision-making, a Fuzzy Logic inference layer was integrated with YOLOv11. The combination of the two techniques contributed to overcoming borderline cases, especially Lytic and Blastic lesions and increased the overall percentage of accurately classified cases to 93.69. The effectiveness of the fuzzy-enhanced system was validated using confusion matrices and comparative analysis across all YOLO versions.
Finally, visual outputs of the detection and classification process were presented, showing accurate bounding-box predictions and class labels. The results clearly highlighted the superiority of the proposed YOLOv11 + Fuzzy Logic framework, making it a strong candidate for clinical decision support in early detection and classification of spinal metastases.

Chapter 5

Engineering Standards and Design Challenges

This chapter presents the engineering standards followed in the project, covering software, hardware, and communication standards. It also points out the societal, environmental, ethical, and sustainability effects of the proposed system. Furthermore, project management considerations, financial analysis and complexity of the engineering problems are also present in the chapter.

5.1 Compliance with the Standards

5.1.1 Software Standards

Standards Followed:

- o Python for readable, maintainable code.
- o PyTorch framework for deep learning model training.
- o Ultralytics YOLO (v5–v12) for object detection.
- o Scikit-fuzzy for fuzzy logic inference.
- o Matplotlib, IPython.display, and Skit-learn for visualization and progress monitoring.

Alternatives Considered:

TensorFlow vs. PyTorch

- o Pros (TensorFlow): Large scale, industry-ready, and large scale production.
- o Cons: Slower learning curve, has less ability to adapt to fast research studies..
- o Pros (PyTorch): Easy to debug, flexible dynamic graphs, researchable.
- o Cons: A little less production environment optimized in certain deployment situations,

Rationale: PyTorch was chosen due to its flexibility and the simplicity of training and reasoning, as well as good community support and support. Scikit-fuzzy has been selected as it is simple and can perform interpretable fuzzy inference.

5.1.2 Hardware Standards

Standards Followed:

Cloud computing with GPU through Google Colab Pro.

GPU system is supported by the NVIDIA Tesla GPU and optional TPU acceleration.

Alternatives Considered:

Local GPU setup (NVIDIA RTX 3090)

- o Pros: Faster training, full hardware control and the capacity to give offline training.

- Cons: Expensive to purchase, maintenance is necessary.

Other cloud platforms (AWS, Kaggle)

- Pros: Scalable, cost effective, maintenance free.
- Cons: small amount of free quota, requires an ability to connect to the internet.

Rationale: Google Colab Pro was decided on due to the price, which is affordable, and the amount of required GPU is offered.power and enables accessibility of data through Google drive with ease.

5.1.3 Communication Standards

Standards Followed:
Google drive as a dataset storage and sharing service.
GitHub is a repository and collaborative development.

Alternatives Considered:
Enterprise-level control in private GitLab servers.
Kaggle Datasets for public dataset sharing.
Rationale: Using Google Drive and GitHub together enabled secure, efficient, and collaborative development with minimal effort.

5.2 Impact on Society, Environment and Sustainability

5.2.1 Impact on Life

The system enhances diagnostic accuracy for spinal metastatic bone cancer, enabling early detection and timely treatment. This contributes to improved patient survival rates, reduced misdiagnosis, and better overall healthcare outcomes.

5.2.2 Impact on Society & Environment

Positive Impacts:
Reduces radiologists workload by providing AI-assisted decision support.
Minimizes unnecessary diagnostic procedures, saving healthcare costs.
Environmental Aspect:
Cloud-based computing minimizes reliance on local physical servers, which reduces energy usage.
Negative Impact:
GPU-intensive training consumes significant energy, adding to carbon footprint.

5.2.3 Ethical Aspects

- Patient privacy is maintained through anonymization of CT scan data.
- Fuzzy logic ensures interpretable AI decisions, aligning with transparency principles.
- Limitation: AI predictions should not replace human expertise but assist clinicians.

5.2.4 Sustainability Plan

- Continuous updates of the dataset will maintain model adaptability.
- Open-source implementation enables community-driven improvements.
- Future integration with hospital PACS systems ensures sustainable clinical deployment.

5.3 Project Management and Financial Analysis

Estimated Cloud-Based Budget:

Table 5.1 : Estimated Budget

Item	Cost (BDT/year)	Notes
Cloud GPU subscription (Colab Pro+)	16800	Capable of supporting model training.
Data storage (Google Drive 200 GB)	4000	Secure and accessible
Open-source software	0	No additional cost
Total	**20800**	

Alternative Local GPU Setup:

NVIDIA RTX 3090 system: 300000 BDT

Electricity & maintenance: 36000 BDT/year

Rationale: The use of cloud based setup means low investment at the start and offers the ability to increase or reduce resources and also makes maintenance easy.

5.4 Complex Engineering Problem

This thesis, "A Deep Learning Framework for Spine Metastatic Bone Cancer Detection Using YOLOv11 and Fuzzy Logic", addresses a Complex Engineering Problem. It is a combination of deep learning and fuzzy logic that classifies spinal CT images and it needs medical imaging, machine learning, and hybrid model design expertise. Challenges include handling noisy and heterogeneous CT data, achieving high accuracy, maintaining interpretability, and ensuring ethical use of patient data. The system should also be optimized to provide computational efficiency and possible expansion to bigger datasets or other types of cancer.

5.4.1 Complex Problem Solving

Table 5.2: Mapping with Complex Engineering Problem.

EP1 Dept of Knowledge	EP2 Range Of Conflicting Requirements	EP3 Depth of Analysis	EP4 Familiarity of Issues	EP5 Extent of Applicable Codes	EP6 Extent Of Stake-holder Involvement	EP7 Interdependence
✓	✓	✓		✓		

Mapping with Knowledge Profile

Table 5.3: Mapping with knowledge Profile.

K1 Natural Science	K2 Mathematics	K3 Engineering Fundamentals	K4 Specialist Knowledge	K5 Engineering Design	K6 Engineering Practice	K7 Comprehension	K8 Research Literature
	✓	✓	✓	✓	✓	✓	✓

5.4.1.1 Justification for EP Attributes Mapping

- **EP1 – Depth of Knowledge Required:**
  Advanced understanding of deep learning, YOLO architecture, fuzzy logic, medical imaging, and statistical evaluation.
- **EP2 – Range of Conflicting Requirements:**
  Accuracy vs. interpretability, model complexity vs. computational efficiency, generalization vs. overfitting.
- **EP3 – Depth of Analysis:**
  Careful analysis of CT scan variability, lesion characteristics, and hybrid model performance.
- **EP5 – Extent of Applicable Codes:**
  The study has strictly provided ethics in handling medical data and thus always followed the research ethics principle allowing ethical treatment of medical data, data privacy, and ethical treatment of the imaging datasets.

5.4.1.2 Justification for Knowledge Profile Mapping

- **K2 – Mathematics:**
  Strong foundation in probability, statistics, and linear algebra supports model training, loss function optimization, fuzzy membership functions, and evaluation metrics such as mAP, precision, and recall.
- **K3 – Engineering Fundamentals:**
  Knowledge of good algorithmic, data organization, probability and linear algebra abilities, without which, the implementation of YOLO models and the use of fuzzy logic would not be possible.
- **K4 – Specialist Knowledge:**
  Strong knowledge of deep learning (YOLO architecture, optimization), medical image processing (CT scans, spine lesion detection) and statistics.
- **K5 – Engineering Design:**
  Developing the hybrid YOLO + fuzzy logic model, loss functions optimization, heterogeneous CT dataset feature engineering and the creation of robust experimental

configurations.

- **K6 – Engineering Practice:**
  Strict experiment design, statistical validation of findings, code and experiment version control, presentation and findings reporting.
- **K7 –** The ability to understand and explain engineering concepts clearly. In this thesis, it is shown by explaining YOLO models, fuzzy integration, and result analysis in a simple way.
- **K8 – Research Literature:**
  The project relies heavily on current research in YOLO, fuzzy logic, and medical imaging. Continuous literature review and contribution to cutting-edge studies are essential.

5.4.2 Engineering Activities

Table 5.4: Mapping with Complex Engineering Activities.

EA1 Range of re-sources	EA2 Level of Interaction	EA3 Innovation	EA4 Consequences for society and environment	EA5 Familiarity
✓		✓	✓	✓

5.4.2.1 Justification for Engineering Activities Mapping:

- **EA1 – Range of Resources:**
  Employs large CT scan datasets, GPU-enabled environments (Google Colab) for model training, deep learning frameworks like Ultralytics YOLO and PyTorch, fuzzy logic tools such as scikit-fuzzy, and relevant academic literature.
- **EA3 – Innovation:**
  Creation of a hybrid YOLO + fuzzy logic framework to detect spine metastatic bone cancer using both deep learning and fuzzy inference frameworks to deal with borderline cases to achieve better accuracy and interpretability..
- **EA4 – Consequences for Society and Environment:**
  Societal: Enhances early detection of spine cancer, reduces misdiagnosis, supports radiologists with AI-assisted decision-making and potentially improves patient outcomes.
  Environmental: Uses cloud computing resources; energy consumption is limited compared to full-scale local infrastructure.
- **EA5 – Familiarity:**
  While image preprocessing, model training, and evaluation use standard procedures, combining YOLO detection with fuzzy logic for medical diagnosis requires innovative problem-solving and design beyond conventional workflows.

5.5 Summary

This chapter explained the engineering requirements used in software, engineering and communication some aspects focusing on rationale and substitutes. It has pointed out the consequences of the system on the society, in morality and the environment and also gave a sustainability plan. Cloud-based implementation was supported by the financial analysis compared to local implementation. Last, the multidisciplinary richness of the project displayed the novel combination of deep learning, fuzzy and medical imaging to detect spinal metastatic bone cancer.

Chapter 6
Conclusion

This chapter completes the research work as it summarizes the contributions, states limitations of the current work, and provides significant options of future enhancement.

6.1 Summary

This thesis introduced a deep learning-based model of the spinal metastatic bone cancer detection and classification with the help of CT images. A combination of YOLOv11 as the feature extraction and object detector neural network, along with a decision-making layer made of fuzzy logic, was designed to obtain improved interpretability and a higher classification rate.The system was trained and tested on a curated dataset with three classes of data, namely the three categories: Normal, Lytic, and Blastic. As was shown in experiments, the offered hybrid structure was both more accurate and stronger than the baseline YOLO models. The experimental study revealed that the layer of fuzzy logic was able to not only enhance the robustness of the classification, but also help make system interpretable. Contrary to the traditional models which present confidence scores only, the fuzzy-like component converted the detection results into membership values (Normal, Lytic, Blastic), which allowed radiologists to have a glimpse of how the system made its decisions.

On the whole, this research showed that a hybrid deep learning and fuzzy logic model may be a convenient tool of diagnostic support to oncologists and radiologists. The framework is a contribution towards the early development of spinal cancer, it minimizes chances of misclassification, and it contributes to increased confidence in AI based medical images analyses. This paper forms the base of subsequent research to develop intelligible AI interfaces to be applicable across clinical care through scaling the model against the interpretability, efficiency and clinical significance precepts.

6.2 Limitation

Despite promising results, the study has several limitations:

- **Dataset Size:** The dataset was relatively small, which may restrict the model's generalization capability to unseen clinical data.
- **Hardware Constraints:** Training was performed on cloud-based GPU resources (Google Colab), limiting model size, training iterations, and hyperparameter tuning.
- **Single Imaging Modality:** The framework relied solely on CT scans. Other modalities such as MRI or PET scans were not considered.
- **Clinical Validation:** The model has not yet been validated in real-world clinical settings

with radiologists.

6.3 Future Work

To address these limitations and strengthen the research, the following directions are recommended:

- **Larger and Diverse Dataset**: The ability to include additional patient information across demographics and institutions to enhance strength and minimize bias..
- **Multi-Modal Integration:** Increasing the framework to support multiple imaging modalities (CT, MRI, PET) in order to diagnose more comprehensively.
- **Advanced Hybrid Models:** Exploring integration with other explainable AI techniques alongside fuzzy logic to further enhance interpretability.
- **Deployment in Healthcare Systems:** Developing a user-friendly software tool or PACS-integrated system for hospital usage.
- **Clinical Trials:** Conducting validation with medical professionals to ensure reliability and acceptance in real-world applications.

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