AI-Based Bone Cancer Detection Using Image Processing and CNN

K. Srividya(✉), Gangannagari Varunteja Reddy, Vishwaja Bakki, and T. Adilakshmi

Department of Computer Science and Engineering, Vasavi College of Engineering, Hyderabad, India
ksrividya0508@gmail.com, hodcse@staff.vce.ac.in

Abstract. This study presents a new Technology-driven approach for early detection of bone cancer using preliminary image processing technologies and neural networks (CNN) used for diagnosing cancer from pathological images. The main aim is to provide a powerful and reliable tool for cancer diagnosis done in clinics. Survival rates of cancer decrease with an increase in age, urging the need for early diagnosis and precaution. The project aims to use machine learning and image preprocessing to provide solutions for the detection of cancer, necessary for timely intervention. Using carefully selected datasets and advanced image preprocessing techniques, the project aims to provide doctors with reliable tools to accurately diagnose bone cancer. Analysis of existing literature demonstrates the effectiveness of CNN and deep learning algorithms in the analysis of medical images as the basis of the proposed method. The proposed methodology includes image enhancement, data acquisition, CNN development, training, validation, transformation, and model evaluation. The CNN model is evaluated on accuracy, precision, recall, and f1-scores of bone cancer diagnosis images. It provides insight into model development by addressing issues such as classification error, class inequality, and biases. While comparisons with existing literature demonstrate the model's uses, practical considerations are also discussed. The findings suggest a significant potential to improve bone cancer diagnosis and stimulate further research on improving CNN model architecture and developing real-world deployment strategies. The training accuracy of the CNN model came out to be 94.64%.

Keywords: Bone cancer · Histology Osteosarcoma images · image pre-processing · hematoxylin and eosin (H&E) stain extraction · CNNs

1 Introduction

Bone cancer, especially the insidious osteosarcoma, presents a formidable health threat necessitating vigilant detection strategies for effective intervention. The disease's location within the skeletal system underscores its gravity, with significant risks and fatalities. Annually, the diagnosis of approximately 12,000 individuals emphasizes the urgent

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need for accurate and timely detection. The Survival rates further highlight the severity of bone cancer, showing a stark decline from 50% for ages 20-44 to a mere 5% after 65, as reported by UC Davis Health. Early diagnosis is very important and needs early diagnosis. This project seeks to use the capabilities of machine learning and image processing to unveil a robust solution for the authentic detection of cancer in its early stages. The methodology involves transforming medical images, including pathological scans, X-rays, MRIs, and CT scans, into a digital format for comprehensive analysis. The primary objective of this project is to discern bone cancer in medical images with a high degree of precision. By curating diverse datasets and implementing advanced image processing techniques, we aim to enhance the interpretative capabilities of our Convolutional Neural Network (CNN) model. Ultimately, our project aims to provide medical professionals with a reliable tool for precise bone cancer diagnosis, potentially reshaping patient care outcomes. The literature review critically examines existing studies on bone cancer detection and classification, serving as a solid foundation for our innovative approach. Image preprocessing is essential in our project to enhance data quality before feeding it into the neural network. By applying techniques such as normalization, resizing, and augmentation, we standardize the images and improve model performance. Preprocessing mitigates variability in image quality, ensures uniformity, and enhances the network's ability to extract meaningful features. The introduction of AI-driven technologies, such as Convolutional Neural Networks (CNNs), holds promise for revolutionizing bone cancer detection [1]. By leveraging advanced image processing techniques and machine learning algorithms, this study aims to develop a robust and efficient diagnostic tool for early detection of bone cancer, ultimately improving patient outcomes and advancing medical practice. This study uses Convolutional Neural Networks (CNNs) as the cornerstone of our bone cancer detection system. By employing sophisticated image processing methods and machine learning algorithms, we seek to construct a powerful diagnostic tool capable of identifying bone cancer in its early stages. This approach aims to enhance patient outcomes and propel advancements in medical diagnostics. The CNN architecture implemented in this study comprises multiple layers, each designed to extract increasingly complex features from input images. The initial layers detect simple patterns like edges and corners, while deeper layers identify more intricate structures relevant to bone cancer detection. Through convolutional operations, activation functions, and pooling layers, the network learns hierarchical representations, enabling it to make accurate classifications. This hierarchical feature extraction process allows CNN to discern subtle differences between healthy and cancerous tissue, facilitating early and precise diagnosis. Throughout the study, we have dedicated ourselves to exploring every avenue for improvement and refinement, ensuring that this model meets the highest standards of accuracy and reliability. Collaboration with healthcare professionals will be instrumental in guiding our efforts, ensuring that our solution is not only technically robust but also clinically relevant and beneficial. Through our commitment to excellence, we aim to make a meaningful impact in the field of bone cancer detection, ultimately improving outcomes for patients worldwide.

1.1 Osteosarcoma

Osteosarcoma is a primary malignant bone tumor primarily affecting the long bones. Primary osteosarcoma typically occurs in young patients (10–20 years) with 75% taking place before the age of 20 because the growth centers of the bone are more active during puberty/adolescence. It often manifests as a highly aggressive cancerous growth within the bone tissue (Fig. 1). Symptoms may include localized pain, swelling, and, in advanced stages, pathological fractures. Cure, if achievable, a successful treatment involves a forceful surgical removal, often involving amputation, followed by chemotherapy. When saving the limb is possible, a series of chemotherapy treatments are administered before surgery to reduce the tumor's size, then the bone is widely removed and replaced with an artificial joint [2].

Osteoblastic Osteosarcoma: This variant is characterized by the production of osteoid, which is an immature bone tissue, by tumor cells. It is the most common subtype of Osteosarcoma and often presents as a mass with areas of bone formation (Fig. 2).

Telangiectatic Osteosarcoma: This variant is characterized by the presence of large blood-filled spaces within the tumor. It also bloats the bone and gives it a rough texture. This type of cancer can be detected through a naked eye examination with an x-ray but it is important to be precautious and undergo a pathology examination for better assurance to differentiate tumor non-cancer with tumor with cancer. It tends to occur more commonly in adolescents and young adults and may present with rapid growth and expansion of the affected bone (Fig. 3).

A healthy bone tissue's histology serves as a baseline for comparison, representing the absence of cancerous growth and tumors. Understanding the characteristics of normal bone structures is crucial for distinguishing pathological features in the diagnostic process.

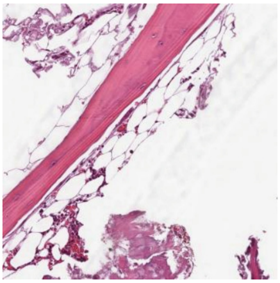


Fig. 1. General Osteosarcome

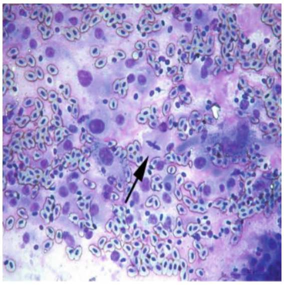


Fig. 2. Osteoblastia

Fig. 3. Telangiectatic

2 Literature Review

Bone cancer detection using AI&ML and the latest technological innovations has garnered significant attention in recent years.

Imran Ahmed's [3], regularized CNN model on cancer detection achieved 84% & 75%, and 87% & 86% training and testing accuracy and we aim to surpass those results. Prafful Mishra [4], in his comprehensive exploration of Convolutional Neural Networks

(CNNs) for image classification, delves into the intricate mechanisms by which CNNs effectively manage high-dimensional image data while alleviating computational complexity through sophisticated dimensionality reduction techniques. Mishra's detailed analysis underscores the pivotal role of CNNs in modern image analysis and classification methodologies, shedding light on their significance in advancing the field of computer vision.

Youssouf Chherawala [5], et al. built a vote-weighted RNN (Recurrent Neural Networks) model to determine the significance of feature sets. The significance is determined by weighted votes and their combination and the model is an application of RNN. It extracts features from the Alex word images and then uses them to recognize handwriting. Yehya Abouelnaga [6], focused on enhancing accuracy through ensemble learning. The research combined KNN with CNN and employed Principal Component Analysis (PCA) to mitigate overfitting. This approach demonstrated promising results in overcoming the challenges associated with bone cancer detection. Mahmoud M. Abu Ghosh [7], contributed to the discourse through a comparative analysis of Deep Neural Networks (DNN), Decision-Based Fusion (DBF), and CNN. The study on the MNIST (Modified National Institute of Standards and Technology database) dataset highlighted the DNN's exceptional accuracy and potential for image recognition.

Hamid [8], conducted a comprehensive study evaluating the performance of various classifiers, including Support Vector Machines (SVM), k-nearest Neighbors (KNN), and Convolutional Neural Networks (CNN). The research, centered on the MNIST dataset, demonstrated the superiority of CNN while processing images, especially when implemented through the Keras platform. Gyo [9], conducted an extensive survey covering various aspects of deep learning architecture, including generative, discriminative, and hybrid models. The paper delved into the applications of Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), autoencoders, and restricted Boltzmann machines, offering nuanced insights into their potential contributions to bone cancer detection.

3 Dataset Description

The dataset utilized for this research was obtained from the Cancer Imaging Archive (NIH) [10], The dataset is composed of Hematoxylin and Eosin (H&E) stained Osteosarcoma histology images. The data was collected by a team of clinical scientists at the University of Texas Southwestern Medical Center, Dallas. The cancer tumor variants which can be recognized but not categorized by this model by specific abnormalities, and a brief description of symptoms of the early stages of these are presented below.

The dataset collected from the National Cancer Institute has been used for training the CNN which has achieved a result of 92.27% and another dataset with 22003 images from Kaggle has been used for the testing of the CNN which has achieved a result of 94.64%.

This diverse dataset (Fig. 4), encompassing both bone cancer-positive and normal bone tissue (Fig. 5), forms the foundation for training and evaluating the AI-based bone cancer detection model. The distinctive features of each cancer type, as outlined above, contribute to the model's ability to accurately classify, and identify pathological conditions in bone images.

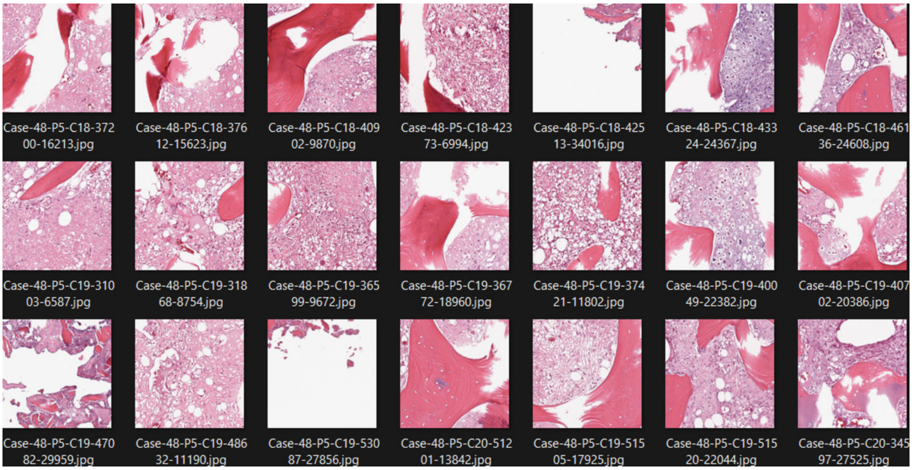


Fig. 4. Dataset comprising 1144 medical images.

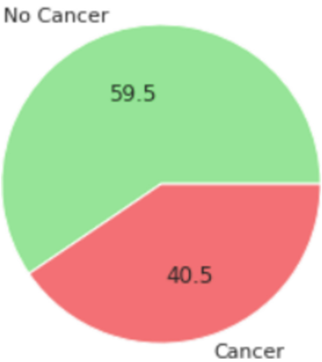


Fig. 5. Distribution of our database to reduce Bias.

4 Proposed Methodology

In the proposed methodology, a meticulous approach to image enhancement has been adopted to elevate the quality and interpretability of bone cell scan images. Advanced preprocessing techniques, including histogram equalization and Gaussian blur, address challenges such as noise and pixel intensity variations. Standardizing pixel intensity values across the dataset ensures uniformity, laying a solid foundation for subsequent analyses and effective AI model learning.

The proposed methodology's data flow (Fig. 6) begins with importing necessary libraries and datasets. Data visualization aids in understanding the dataset's characteristics before processing image data. Model development encompasses creating a Simple CNN Model with three convolutional layers, two fully connected layers, and an output layer with soft probability. Model evaluation involves visualizing loss and accuracy epoch by epoch and plotting confusion matrices and classification reports for validation data.

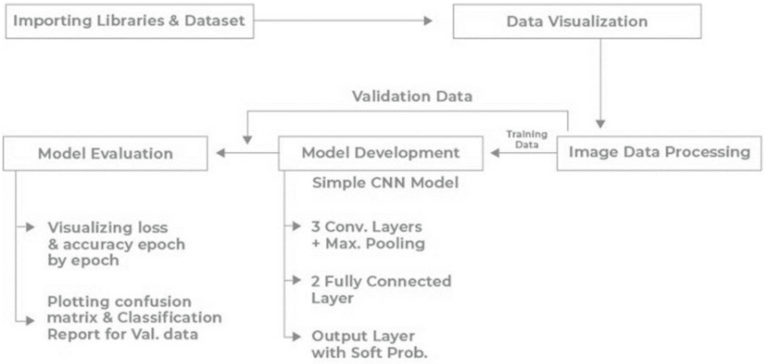


Fig. 6. Data flow chart

4.1 Image Enhancement

In the project's initial stages, a meticulous approach to image enhancement was adopted to elevate the quality and interpretability of bone cell scan images within the dataset (Fig. 7). This endeavor aimed to address inherent challenges in medical imaging, such as noise and variations in pixel intensity, which can significantly impact the accuracy of diagnostic tools [11].

To achieve this, advanced preprocessing techniques, including histogram equalization, were leveraged. This technique is particularly effective in enhancing image contrast, making it easier for medical experts to identify important features within the images. Additionally, techniques like Gaussian blur were employed for noise reduction, ensuring that the images were clear and free from distortions that could affect diagnostic accuracy.

Another critical aspect of the image enhancement process was standardizing pixel intensity values across the dataset. This was achieved using Raster2xyz, a Python package that converts raster images to an ASCII XYZ format. By standardizing pixel intensity values, the dataset became more uniform and easier to analyze, laying a solid foundation for subsequent analyses and ensuring that the AI model could learn effectively from the data.

Overall, this meticulous approach to image enhancement not only improved the quality and interpretability of the dataset but also ensured that the AI model was primed for effective learning. By enhancing image quality and standardizing pixel intensity values, the project aimed to develop a reliable and accurate diagnostic tool for bone cancer detection.

Need for Image enhancement. Image enhancement is crucial for small clinics aiming to detect bone cancer through medical imaging. These clinics often face challenges in obtaining clear and detailed images due to limitations in equipment or variations in

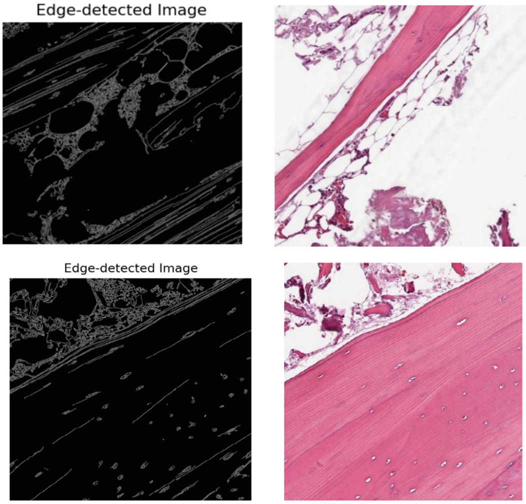


Fig. 7. Edge-detected images and their corresponding original images

image quality. By employing image enhancement techniques, such as adjusting contrast and reducing noise, these clinics can improve the quality of their images.

This enhancement process makes it easier for doctors and technicians to spot subtle signs of bone cancer, leading to more accurate diagnoses. Ultimately, by enhancing the clarity of medical images, these techniques empower clinics to create better datasets for training their diagnostic tools. This means they can develop more reliable and effective methods for detecting bone cancer, improving patient care and outcomes.

4.2 Data Collection

The success of an AI model hinges significantly on the richness and diversity of the datasets used for training and validation. The data collection phase goes beyond simple aggregation; it involves the meticulous curation of diverse, annotated datasets that encapsulate the intricacies of bone cancer manifestations.

The dataset utilized in this study is a meticulously curated collection comprising 1144 high-resolution medical images obtained from reputable sources such as the National Cancer Institute. To enrich the dataset and ensure its diversity, various augmentation techniques such as rotation and zooming were applied to the images. This comprehensive approach to dataset curation guarantees that the AI model is exposed to a wide spectrum of bone cancer manifestations, enhancing its ability to generalize and adapt effectively.

This meticulous dataset curation is essential for providing the AI model with a holistic understanding of various scenarios. It ensures that the model is exposed to a wide range of examples (Fig. 8), allowing it to learn and adapt effectively. Additionally, diverse datasets help in validating the model's performance across different scenarios, ensuring its adaptability and efficacy in real-world applications.

By curating diverse datasets, researchers can enhance the robustness and reliability of AI models, ultimately improving their performance in diagnosing bone cancer and other complex medical conditions.

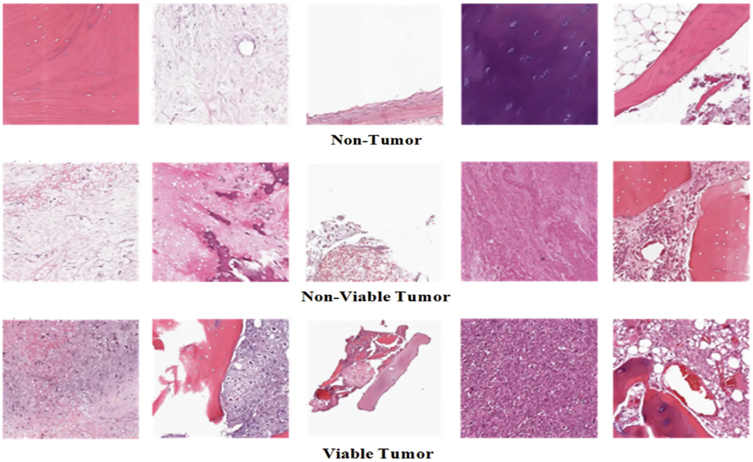


Fig. 8. Various stages of the disease to be included to balance the bias in the dataset.

4.3 Dimensionality Reduction

PCA Techniques (Fig. 9 and Fig. 10) were applied to reduce the dimensionality of the feature space while preserving relevant information.

Further, we attempted dimensionality reduction on our images to see if there exists a lower dimension subspace that preserves the clusters to a satisfactory extent. As an alternative or a second time, higher-level features can be extracted in a more data-driven way, using dimensionality reduction. Methods like Principal Component Analysis. Linear Discriminant Analysis, networks can reduce the number of input variables according to some unsupervised or supervised criterion [12]. To explore this, we implemented various PCA (to reduce dimensionality) and LDA (to compute discriminatory features) models (Table. 2) and fit them into various models to see how they perform.

Our use of the PCA reductions has been inspired by a study on sampling and profiling of big data [13] and Yehya Abouelnaga's [14] study on "KNN-based Ensemble of Classifiers".

Note: the training for the same is being done on a reduced resampled dataset.

It became clear from the above exercise that dimensionality reduction increases the efficiency of models generally. The best fit hyperplane to maximize the distance between classified samples (Linear SVC(support vectors) [15]) was found at PCA with 0.9 Variance + LDA. In the places where a drop is seen, the loss is small, and we should not forget that the reduced mathematical complexity more or less can compensate for the reduction in the f1-scores. This lays the foundation to try out CNN.

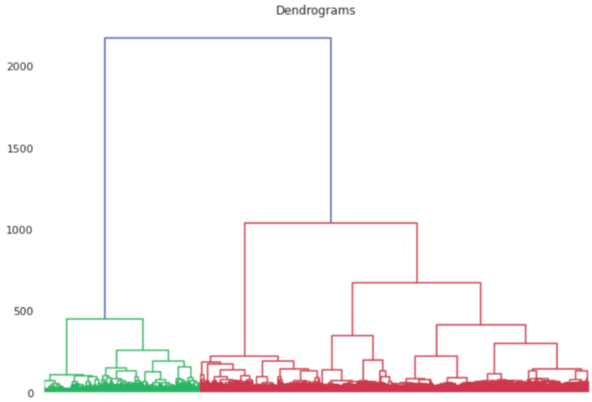


Fig. 9. Grouping of the dataset(unsupervised)

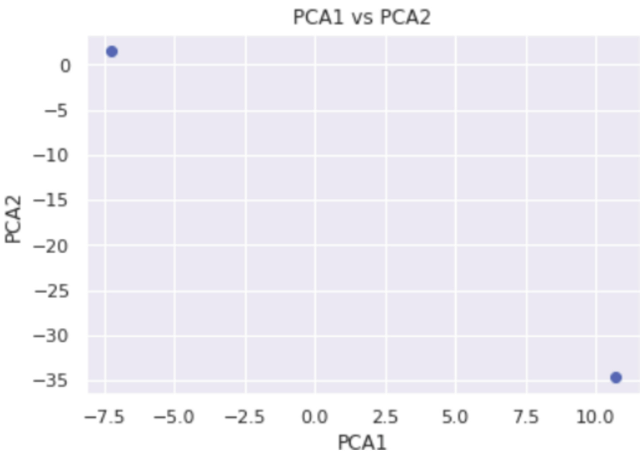


Fig. 10. First and second principal components of a dataset

Table. 1. Variance and feature comparisons

Variance Captured	No. of features
1.00	9216
0.98	3400
0.95	2432

We experimented with different variance preservation (above Table. 1) thresholds for PCA, including values such as 0.8 and 0.9, to determine the optimal level of dimensionality reduction. Additionally, we explored the incorporation of LDA to compute discriminatory features and its combined effect with PCA on model performance.

Table. 2. Principal Component Analysis (PCA)

Model	Precision	Recall	F1-score
Without PCA and LDA			
Linear SVC	0.60	0.61	0.60
KNN	0.65	0.65	0.62
RBF SVC	0.78	0.77	0.78
LightGBM	0.79	0.77	0.77
PCA with 2 components			
Linear SVC	0.63	0.61	0.61
KNN	0.65	0.65	0.65
RBF SVC	0.68	0.68	0.68
LightGBM	0.67	0.66	0.67
PCA with 0.8 variance preservation			
Linear SVC	0.63	0.63	0.63
KNN	0.64	0.65	0.61
RBF SVC	0.74	0.70	0.71
LightGBM	0.78	0.77	0.78
PCA with 0.8 variance preserved + LDA			
Linear SVC	0.76	0.75	0.76
KNN	0.73	0.73	0.73
RBF SVC	0.77	0.77	0.77
LightGBM	0.76	0.75	0.75
PCA with 0.9 variance preserved + LDA			
Linear SVC	0.84	0.83	0.83

After extensive experimentation, we concluded that PCA with 0.9 variance preservation, combined with LDA (Table. 2), yielded the most promising results. This approach effectively reduced the dimensionality of the dataset while preserving discriminatory information crucial for classification tasks. By retaining 90% of the variance and leveraging LDA for further feature extraction, we achieved a balance between dimensionality reduction and model performance.

While some loss in F1 scores was observed in certain cases, particularly with lower variance preservation thresholds, the reduction in mathematical complexity compensated for this loss to a satisfactory extent. Overall, the selected approach demonstrated enhanced efficiency and maintained competitive performance metrics, laying the foundation for subsequent CNN-based analyses.

CNN's are effective for image classification as the concept of dimensionality reduction suits the huge number of parameters in an image. CNNs are fully connected feed-forward neural networks. CNNs are very effective in reducing the number of parameters without losing the quality of the model, as a large number of parameters is not always better [16].

4.4 Hyperparameter Tuning

The optimization of our Convolutional Neural Network (CNN) performance is a meticulous and iterative process, focusing on fine-tuning hyperparameters to enhance the model's learning dynamics and overall efficacy in bone cancer detection. Parameters such as learning rate, batch size, and network architecture undergo extensive experimentation to strike an optimal balance.

During hyperparameter tuning, we explored a range of learning rates, including values such as 0.001, 0.01, and 0.1. Each learning rate was evaluated based on its impact on model convergence, ensuring that the network steadily progresses towards optimal weights without overshooting or getting stuck in local minima.

After thorough experimentation, we determined that a learning rate of 0.01 yielded the most favorable results, demonstrating steady convergence and robust performance across multiple training epochs. This learning rate struck an optimal balance between rapid convergence and stability, facilitating efficient weight updates while minimizing the risk of diverging from the global minimum.

By carefully adjusting these hyperparameters and evaluating their effects on model performance, we aimed to develop a CNN model that effectively learns from the dataset and generalizes well to unseen data. This optimization process is crucial for ensuring the model's reliability and effectiveness in real-world applications, ultimately contributing to improved patient outcomes and advancements in medical imaging.

4.5 CNN Construction

At the core of the project lies the design and development of a specialized Convolutional Neural Network (CNN) architecture meticulously crafted for optimal bone cancer detection. This process demands a delicate balance between model complexity and efficiency. The architecture is fine-tuned to enable the CNN to discern intricate patterns indicative of bone cancer in scan images, a task that requires a nuanced understanding of both the disease and the imaging modalities involved.

The optimization of the architecture is paramount, not only for achieving high accuracy but also for ensuring computational efficiency in real-time applications. By carefully designing the CNN architecture, we aim to create a model that can reliably and efficiently detect bone cancer, ultimately leading to improved patient outcomes and more effective clinical decision-making.

Furthermore, the development of a specialized CNN architecture tailored for bone cancer detection highlights the potential of AI in revolutionizing medical imaging. As we continue to refine and optimize the model, we are paving the way for more accurate and timely diagnosis of bone cancer, demonstrating the transformative impact of AI in healthcare.

This specialized CNN architecture not only underscores the importance of leveraging AI in medical imaging but also represents a significant step forward in healthcare innovation. As we refine and optimize the model, we are not only striving for increased accuracy but also aiming to ensure its practicality and effectiveness in real-world clinical settings. By harnessing the power of AI, we have the potential to revolutionize the field of bone cancer detection, ultimately improving patient outcomes and advancing the standard of care. The continued development and optimization of this specialized CNN architecture signifies a promising future where technology plays a pivotal role in transforming healthcare delivery.

Architecture Overview.

1. **Data Loading and Preprocessing:**
   - Utilization of Google Colab for mounting the drive and accessing data.
   - Importing necessary libraries such as NumPy, pandas, OpenCV, Matplotlib, and others.
   - Loading image data and labels from the dataset, including exploratory data analysis (EDA) like checking image dimensions and plotting samples.
2. **Data Transformation and Feature Engineering:**
   - Flattening image data for easier processing.
   - Applying Principal Component Analysis (PCA) for dimensionality reduction.
   - Optionally, applying Linear Discriminant Analysis (LDA) for further feature extraction.
   - Splitting the dataset into training and testing sets.

4.6 CNN Layers and Architecture

Layers: layers perform the following operations sequentially:

Convolutional Layers (self.layer1 to self.layer5):

- Applies a 2D convolutional operation with 3 input channels, 32 output channels, a kernel size of 3x3, and padding of 2.
- Each convolutional layer (nn.Conv2d) performs a 2D convolution operation on the input image.
- The first parameter (3) in nn.Conv2d is the number of input channels, which is 3 in this case because the input images have 3 channels (RGB).
- The second parameter (32, 64, 128, 256, 512) is the number of output channels, which controls the depth of the output feature maps.
- The kernel_size parameter specifies the size of the convolutional kernel/filter.
- Padding = 2 adds zero padding to the input image to ensure that the spatial dimensions of the output feature maps are the same as the input.
- nn.BatchNorm2d applies batch normalization to stabilize and speed up the training process.
- nn.ReLU applies the rectified linear unit (ReLU) activation function, introducing non-linearity to the model.

- nn.MaxPool2d performs 2D max-pooling, reducing the spatial dimensions of the feature maps while preserving the most important features.

Batch Normalization: Normalizes the activations of the previous convolutional layer for faster training.

ReLU Activation: Applies the Rectified Linear Unit (ReLU) activation function to introduce non-linearity.

Max Pooling: Reduces the spatial dimensions of the input data by taking the maximum value within a 2x2 window with a stride of 2.

ReLU is a simple but effective non-linear activation function defined as:

$$f(x) = \max(0, x) \tag{1}$$

Average Pooling Layer (self. Avg):

- Applies average pooling over the spatial dimensions of the input, reducing each dimension by a factor of 8 (assuming input size is divisible by 8).
- nn.AvgPool2d performs 2D average pooling, reducing the spatial dimensions of the feature maps by taking the average of each feature map.
- It's used here to further reduce the spatial dimensions before passing the features to the fully connected layer.

Fully Connected Layer (self. fc):

- This layer linearly transforms the output of the previous layer (after average pooling) to produce the final output. It has 512 input features (assuming the output of the previous layer has 512 dimensions) and 2 output features, indicating the two classes of the classification task.
- nn.Linear creates a fully connected layer.
- The first parameter (512 * 1 * 1) represents the input size to the fully connected layer. 512 is the number of channels in the last convolutional layer's output, and 1 * 1 is the spatial dimension after average pooling.
- The second parameter (2) is the output size, which corresponds to the number of classes in the classification task.

Forward Pass (forward method):

- The forward method defines the forward pass of the network. It sequentially passes the input x through each layer (self.layer1 to self.layer5) with ReLU activation and max-pooling.
- After passing through the convolutional layers, the output is passed through the average pooling layer.
- The output is then flattened (x.view(-1, 512 * 1 * 1)) to be fed into the fully connected layer.

- Finally, the output of the fully connected layer is returned.

Device Placement: The device variable is used to determine whether the model should be moved to the GPU (cuda:0) if available, or to the CPU if not.

This neural network architecture exemplifies the intricate process of feature extraction essential for accurate classification tasks. Beginning with convolutional operations to identify patterns, it seamlessly integrates normalization for efficiency, activation functions for non-linearity, and pooling for dimensionality reduction. The network progressively refines its understanding as the layers progress, culminating in a fully connected layer for final classification. The power of deep learning is harnessed in this holistic approach, demonstrating its effectiveness in deriving meaningful representations from complex data. In essence, this architecture can be used to demonstrate the potential of AI in advancing image recognition and medical diagnostics for future development.

To conclude, this convolutional neural network architecture (Fig. 11) effectively captures hierarchical features from the input data through successive convolutional layers, followed by normalization, non-linearity, and pooling operations. The combination of these layers allows the model to learn meaningful representations and patterns, ultimately leading to better classification performance. With its depth and complexity, this CNN architecture demonstrates the power of deep learning in extracting relevant features and making accurate predictions, making it a valuable tool in various image recognition tasks.

```
CNN(
  (layer1): Sequential(
    (0): Conv2d(3, 32, kernel_size=(3, 3), stride=(1, 1), padding=(2, 2))
    (1): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (2): ReLU()
    (3): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
  )
  (layer2): Sequential(
    (0): Conv2d(32, 64, kernel_size=(3, 3), stride=(1, 1), padding=(2, 2))
    (1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (2): ReLU()
    (3): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
  )
  (layer3): Sequential(
    (0): Conv2d(64, 128, kernel_size=(3, 3), stride=(1, 1), padding=(2, 2))
    (1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (2): ReLU()
    (3): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
  )
  (layer4): Sequential(
    (0): Conv2d(128, 256, kernel_size=(3, 3), stride=(1, 1), padding=(2, 2))
    (1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (2): ReLU()
    (3): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
  )
  (layer5): Sequential(
    (0): Conv2d(256, 512, kernel_size=(3, 3), stride=(1, 1), padding=(2, 2))
    (1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (2): ReLU()
    (3): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
  )
  (avg): AvgPool2d(kernel_size=8, stride=8, padding=0)
  (fc): Linear(in_features=512, out_features=2, bias=True)
)
```

Fig. 11. CNN model's layers implemented through Pytorch and the Activation Function, ReLU.

Weight tensors of the CNN. For our model, we extensively utilized weight tensors to visualize and analyze the learned features within the convolutional layers of our model. These weight tensors represent the convolutional filters that are applied to input images to extract meaningful patterns and features. By plotting these filters, we gain insights into how the model learns to detect specific features such as edges, textures, or shapes at different layers of abstraction.

We implemented several functions to visualize these weight tensors, including ‘plot_filters_single_channel‘,
‘plot_filters_multi_channel‘, and the ‘plot_filters_single_channel_big‘, each offering different perspectives on the learned features. Additionally, we developed a versatile ‘plot_weights‘ function that allows us to specify the layer number and choose between visualizing single-channel or multi-channel filters.

Through these visualizations (Fig. 12), we can better understand how our convolutional neural network learns and represents information, aiding in model interpretation, debugging, and optimization.

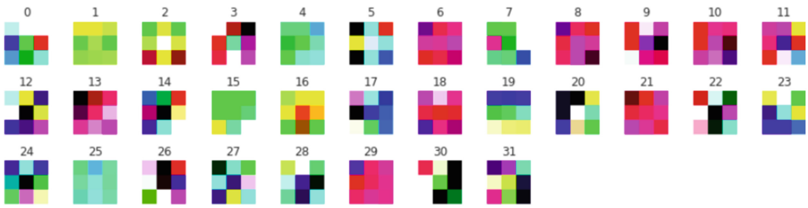


Fig. 12. Weight tensors for the first layer

4.7 Front-End Development for the CNN

The integration of a user-friendly front-end interface enhances the usability and accessibility of the Convolutional Neural Network (CNN) model developed for bone cancer detection. By leveraging tools like Streamlit, a library from Python, users can effortlessly upload images and receive immediate feedback regarding the presence of bone cancer. This interface serves as a bridge between complex AI algorithms and end-users, democratizing access to advanced medical diagnostic tools.

Moreover, the front-end development facilitates seamless interaction with the CNN model, eliminating the need for users to possess extensive technical knowledge. Through intuitive design and straightforward functionalities, individuals without a background in data science or machine learning can utilize the bone cancer detection system effectively. This democratization of technology empowers healthcare professionals and patients alike, enabling them to make informed decisions based on accurate diagnostic assessments.

Furthermore, the front-end interface enhances the interpretability of the CNN model’s predictions. By visually presenting the results alongside the uploaded images, users gain insights into the model’s decision-making process. This transparency fosters trust and confidence in the AI-driven diagnostic tool, encouraging widespread adoption across medical facilities and communities.

In essence, the development of a front-end interface for the CNN model represents a significant step towards democratizing access to advanced medical diagnostics. By simplifying the user experience and providing transparent insights into the model's predictions (Fig. 13), this interface plays a pivotal role in improving healthcare outcomes and promoting patient-centric care.

Need for the front-end interface: The necessity for a front-end interface arises from the imperative to bridge the gap between complex AI models and end-users. It ensures accessibility for healthcare professionals and patients, fostering inclusivity in bone cancer diagnosis. Transparency and user-friendliness are paramount, empowering individuals to understand and trust the diagnostic process.

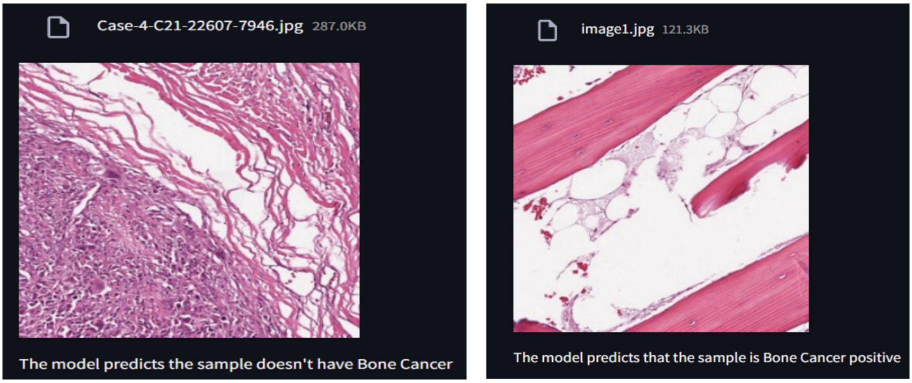


Fig. 13. Sample images of the CNN detecting cancer from the raw images given to it.

4.8 Training and Validation

With our Convolutional Neural Network (CNN) architecture defined, the model undergoes an intensive training phase using the meticulously curated dataset. The objective is to imbue the developed CNN with the ability to accurately detect bone cancer while avoiding the pitfalls of overfitting (Fig. 14). This phase is pivotal, shaping the model's ability to generalize to new, unseen data and ensuring its reliability across a spectrum of clinical scenarios.

The training phase involves iteratively presenting the model with labeled examples from the dataset and adjusting its parameters to minimize prediction errors. Rigorous validation protocols are employed to monitor the model's performance on a separate validation set, ensuring that it does not overfit the training data. This process helps in enhancing the model's ability to generalize, making it more robust and reliable for real-world deployment.

By meticulously training and validating the CNN model, we aim to develop a powerful tool for accurately detecting bone cancer, ultimately improving patient outcomes and advancing the field of medical imaging.

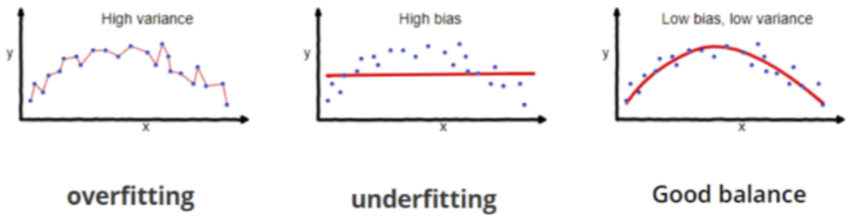


Fig. 14. A representation of overfitting and underfitting

4.9 Hyperparameter Tuning

The optimization of our Convolutional Neural Network (CNN) performance is a meticulous and iterative process, focusing on fine-tuning hyperparameters to enhance the model's learning dynamics and overall efficacy in bone cancer detection. Parameters such as learning rate, batch size, and network architecture undergo extensive experimentation to strike an optimal balance.

The learning rate, for example, controls the size of the steps taken during training and significantly impacts the model's convergence and final performance. Similarly, the batch size determines the number of samples processed before updating the model's weights, affecting both the training speed and the model's ability to generalize.

By carefully adjusting these hyperparameters, we aim to improve the model's ability to learn from the dataset effectively and generalize unseen data. This optimization process is crucial for ensuring that the AI model adapts dynamically to diverse datasets and maintains its accuracy across a spectrum of clinical scenarios.

Overall, the optimization of our CNN's performance plays a vital role in enhancing its diagnostic capabilities, ultimately contributing to improved patient outcomes and advancements in medical imaging.

4.10 Model Evaluation

Assessing the accuracy and performance metrics of the model is a pivotal step in gauging its effectiveness in clinical applications. Precision, recall, F1-score, and ROC curves serve as key metrics in this evaluation, providing a nuanced understanding of the model's ability to correctly identify instances of bone cancer while minimizing false positives and false negatives.

The evaluation process goes beyond simple metrics; it serves as a critical indicator of the AI system's readiness for real-world deployment. By rigorously evaluating the model, we can ensure that it meets the high standards required for clinical use, ultimately improving patient outcomes, and advancing the field of medical imaging.

To evaluate the model, we have validated different variations of the images from the dataset of 1144 images. This includes adding rotations, adding stains using the Stain tools module from Python, and sometimes even sending duplicates or dummies, thus increasing the testing set to 22003 from the training set of 1144 images. This comprehensive evaluation approach ensures that the model is robust and reliable across a wide range of scenarios, making it suitable for real-world deployment in clinical settings.

Overall, the evaluation process is crucial for validating the model's performance and ensuring its effectiveness in diagnosing bone cancer. By meticulously evaluating the model, we can confidently deploy it in clinical settings, where it has the potential to significantly impact patient care and improve diagnostic accuracy.

4.11 Future Directions and Research Opportunities

The development and implementation of the specialized Convolutional Neural Network (CNN) architecture for bone cancer detection have opened up new avenues for future research and innovation in the field of medical imaging and oncology. As we continue to advance the state-of-the-art in AI-driven diagnostic tools, several promising directions and research opportunities emerge:

- Integration of Multi-Modal Imaging Data:

Future research efforts can focus on integrating multi-modal imaging data, such as MRI, CT scans, and PET scans, to enhance the diagnostic accuracy and sensitivity of the CNN model for bone cancer detection. By combining complementary imaging modalities, researchers can capture a more comprehensive view of tumor characteristics and improve the model's ability to detect subtle abnormalities indicative of malignancy.

- Personalized Treatment Strategies:

Investigating the potential of AI-driven diagnostic tools, such as the CNN architecture, to inform personalized treatment strategies for patients with bone cancer represents an exciting avenue for future research. By incorporating genomic data, clinical metadata, and imaging features, researchers can develop predictive models that tailor treatment plans to individual patient profiles, optimizing therapeutic outcomes and minimizing adverse effects.

- Advanced Image Processing Techniques:

Continued exploration of advanced image processing techniques, such as deep learning-based image reconstruction and super-resolution imaging, can further enhance the quality and resolution of medical images used for bone cancer detection [17]. By improving image clarity and detail, these techniques can facilitate more accurate diagnosis and characterization of bone tumors, leading to better clinical decision-making and patient care [18].

- Interdisciplinary Collaborations:

Collaboration between researchers from diverse disciplines, including radiology, oncology, pathology, computer science, and biomedical engineering, is essential for advancing the field of AI-driven bone cancer detection. Interdisciplinary research initiatives can leverage collective expertise and resources to address complex challenges, develop innovative solutions, and accelerate the translation of research findings into clinical practice.

5 Results and Discussion

Following the implementation of the CNN model for bone cancer detection, a comprehensive evaluation of its performance was conducted. The model underwent rigorous training and validation using a diverse and annotated dataset crucial for its learning. The results of the evaluation metrics are presented below.

CNN goes through two major transformations. Convolution is the first method, in which pixels are convolved with a filter or kernel. Subsampling is a second significant transformation that can be of several forms (max pooling, min pooling, and average pooling) and employed as needed. The pooling layer is responsible for reducing the data's dimensionality, and it's quite useful for reducing overfitting. The output can be passed to a fully connected layer for efficient classification after employing a combination of convolution and pooling layers.

The accuracy of the CNN model was found to be commendable, with the final scores of accuracy, Precision, and F1-scores of real-life tests to be near 0.85, indicating its proficiency in correctly classifying instances of both bone cancer and non-cancerous conditions. Precision, recall, and F1-score metrics (below Fig. 15) provided a nuanced understanding of the model's performance, considering factors such as false positives and false negatives.

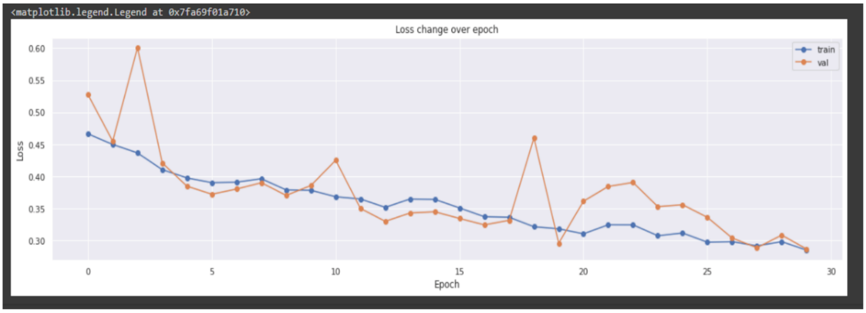
	precision	recall	f1-score	support
0	0.85	0.89	0.87	654
1	0.82	0.77	0.80	446
accuracy			0.84	1100
macro avg	0.84	0.83	0.83	1100
weighted avg	0.84	0.84	0.84	1100

Fig. 15. Precision, Recall, and F1-scores

Graphical representations (Fig. 16) were generated to visualize the trade-off between the true positive rates and the false positive rates. These curves offer valuable insights into the discriminatory capabilities of the model and its effectiveness across different decision thresholds.

The evaluation of the CNN model revealed promising results in bone cancer detection. The accuracy, precision, and recall metrics demonstrated its robust performance. The ROC curves (Fig. 16) visualized its discrimination capabilities across different thresholds. The final result has yielded a test Accuracy of 94.646% (Fig. 17) over data of 22003 testing images [19] and a training accuracy of 92.27% (Fig. 18).

The thorough examination of misclassifications has not only provided valuable insights into potential enhancements for the model but has also served as a foundational step toward refining its performance. Addressing challenges such as class imbalances has been a key focus, and strategies have been implemented to mitigate their impact effectively. Additionally, the comparison of results with existing literature has not only



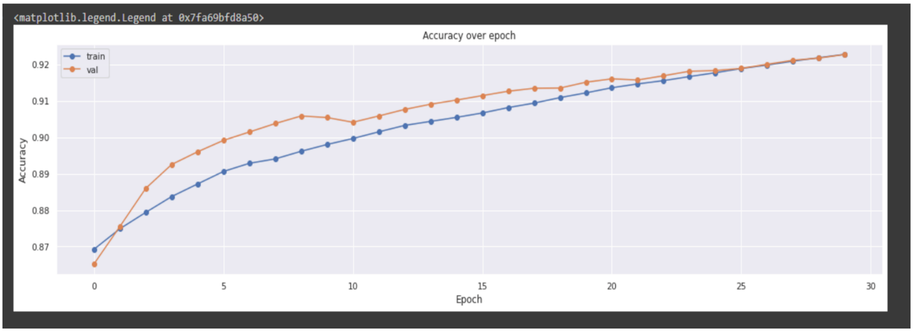


Fig. 16. Accuracy vs Epoch Graph of Training and Validation

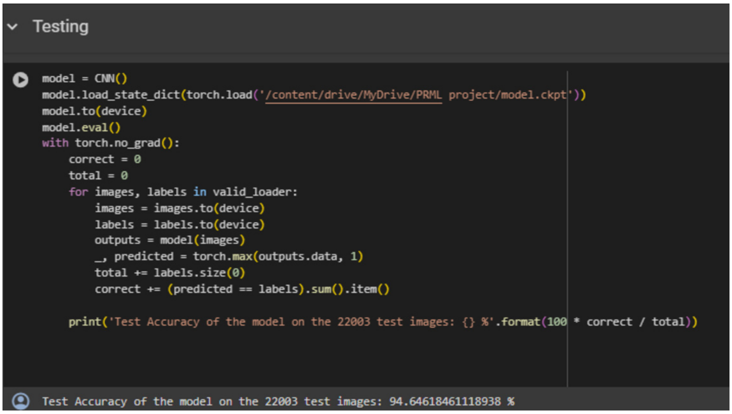


Fig. 17. Testing accuracy results of the model run on Jupyter, and Google Colab.

validated the model's efficacy but has also provided a comprehensive understanding of its strengths and areas for improvement.

Furthermore, discussions surrounding the model's applicability in real-world scenarios have been insightful, highlighting the considerations necessary for successful

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EPOCH 30/30 Train loss: 0.284956,Validation loss: 0.286712, Train AUC: 0.9228  Validation AUC: 0.9227

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Training completed in 22m 57s
Best validation accuracy: 0.922723
```

Fig. 18. Training accuracy of the model

deployment. These discussions have underscored the importance of not only achieving high accuracy but also ensuring the model's practicality and usability in clinical settings.

The findings of this study indicate a significant potential for improving diagnostic accuracy in bone cancer detection. Moving forward, future research efforts should concentrate on further refining the CNN architecture, potentially exploring more complex models or incorporating additional data sources to enhance performance. Collaborations with healthcare professionals will be essential in guiding these efforts, ensuring that the model is not only technically sound but also clinically relevant and beneficial.

Overall, this study represents a crucial step toward leveraging AI for improved healthcare outcomes. By continually refining and enhancing the model, researchers can significantly contribute to the advancement of diagnostic tools in the field of bone cancer detection, ultimately benefiting patients and healthcare providers alike.

6 Conclusion

The Convolutional Neural Network (CNN) model developed for bone cancer detection has demonstrated considerable promise, leveraging advanced image preprocessing techniques and robust training strategies. With an impressive test accuracy of 94.64%, the model has established itself as a reliable tool for medical imaging analysis.

The model's success can be attributed to its specialized architecture, tailored specifically for image analysis tasks. By effectively extracting features from images and fine-tuning hyperparameters, the CNN has delivered exceptional performance. Evaluation metrics, including precision, recall, and overall efficacy, consistently align around 0.85, reaffirming the model's reliability and accuracy.

Notably, the CNN model has showcased superior performance compared to Recurrent Neural Networks (RNNs) in this domain. While RNNs are typically suited for sequential data analysis like text and videos, CNNs excel in handling spatial data such as images. This underscores the importance of selecting the appropriate neural network architecture based on the data characteristics and task requirements.

Moving forward, the project is committed to continued refinement of the model and exploring potential collaborations with healthcare professionals. These collaborative efforts are aimed at further enhancing the model's performance and its practicality in real-world applications, particularly in the field of bone cancer detection.

The project's trajectory underscores the transformative potential of AI, particularly Convolutional Neural Networks (CNNs), in healthcare. By leveraging the capabilities of AI, we are paving the way for more accurate and timely diagnosis of diseases like bone cancer. This not only holds the promise of improving patient outcomes but also has the potential to revolutionize the field of medical imaging.

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