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X-ray body Part Classification Using Custom CNN

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Abstract

INTRODUCTION: This work represents a significant step forward by harnessing the power of deep learning to classify X-ray images into distinct body parts. Over the years X-ray pictures were evaluated manually.
OBJECTIVE: Our aim is to automate X-ray interpretation using deep learning techniques.
METHOD: Leveraging cutting-edge frameworks such as FastAI and TensorFlow, a Convolutional Neural Network (CNN) has been meticulously trained on a dataset comprising DICOM images and their corresponding labels.
RESULT: The results achieved by the model are indeed promising, as it demonstrates a remarkable ability to accurately identify various body parts. CNN shows 97.38% performance by compared with other classifiers.
CONCLUSION: This innovation holds the potential to revolutionize medical diagnosis and treatment planning through the automation of image analysis, marking a substantial leap forward in the field of healthcare technology.

Keywords: Analyze X-ray images, CNN, Classification of X-ray Body Parts

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1. Introduction

As in 21st century medical emergencies have increased and this generation have been affected with COVID-19 where there were massive causes over all hospitals due to in availability of equipment's here as imaging data's are clinical and collected and preserved in databases for diagnostically feature relevant information's few clinics in towns are struggling in burden of diagnosis here this technology will help the health sector officials for efficient capabilities of the causes.

In this paper, we created a clever system that can analyse X-ray images and identify the body portion to which they belong. It can tell, for instance, if an X-ray depicts the hand, ankle, or chest. Etc. Deep learning is similar to teaching a computer's brain to spot patterns and make judgement calls in the same way that people learn through experience. We gathered a significant number of X-ray images as well as details on which body part each image corresponds to in order to train the system. We also have a list of labels for each X-ray that identify the bodily portion to which it belongs, and these images are saved in a unique format called DICOM.

Then, after processing, we uniformly sized, brightened, and contrasted these pictures. This phase is crucial for the computer to readily comprehend and compare all of the photos. The next step was to construct a convolutional neural network (CNN). This CNN functions as a smart filter that can examine the images, identify key details, and forecast which body part is seen in the X-ray.

The processed images and their related labels were used to train the CNN. It gained knowledge from countless examples so that it could identify the X-ray patterns associated with various body regions. After training, we put the CNN to the test using brand-new, unveiled X-ray images. The model mostly correctly identified the right bodily components, which was a positive outcome. This innovative technique can assist doctors swiftly analyse X-rays, leading to quicker and more precise diagnosis. By automating the process of locating certain body areas in X-ray images, it may be possible to reduce time and enhance patient care.

2. Related Work

X-rays were first used for medical imaging in the late 19th century after Wilhelm Conrad Roentgen made the discovery in 1895. Since that time, X-rays have developed into one of the most popular diagnostic instruments in medicine. X-rays were originally primarily utilized for bone imaging, but as technology has advanced, they have also been used to see other soft tissues and organs [15].

The norm over the years has been for radiologists to manually evaluate X-ray pictures. However, when machine learning and artificial intelligence tools developed, researchers began looking into automated X-ray interpretation approaches. Convolutional neural networks (CNNs), a deep learning technology, are used to automatically detect and categorize various body parts in X-ray scans in the process of body part classification from X-ray pictures. These systems learn to identify patterns related to different body parts using massive datasets of annotated X-ray pictures [1][2].

The project's goal is to obtain bodily parts, identify any defects compared to a stable, proper part, and disclose the component's name and the location of the fault. This application is most frequently used in the medical industry since it uses machine learning to identify and designate body parts. Most people today have multiple fractures of bones, breathing issues, etc. Consequently, this project is crucial to diagnosis. This study demonstrates how using artificial intelligence, in particular Convolutional Neural Networks, can assist radiologists diagnose patients more accurately by detecting certain things in chest x-ray images [1].

Yabsera Erdaw et al. have proposed a detection algorithm using a machine learning approach, where their idea of implementing and proposing the model is chest X-ray images that allow automatic detection of COVID-19 cases, and they have designed with a superior accuracy here. The advantage is that they use dynamic datasets from which they can obtain real-time data [1].

Moshe Aboud et al. For upcoming clinical procedures, this study paper has suggested analyzing automatic categorization using significant amounts of x-ray picture data. They have divided the study into distinct sections, such as the head, neck, and limbs, which include upper, lower, and other, and have suggested using ImageCLEF-2015 to cluster the data points. Here, they use feature extraction techniques, include them into image classifications, and optimize them to show bone form and size. With texturing, HoG features, and KNN Classifier, they got good results. According to this study, they were able to attain 73% to 86% accuracy using only 1000 training photos and 500 testing images [2].

Boran Sekeroglu et al. have proposed the concept of deep learning using a convolutional neural network [CNN] that can detect the presence of COVID-19 in the body part. They employed "ConvNet," which had four layers with relu activated, and their method achieved a mean accuracy of 98 percent. Here, they have employed a static dataset to develop the methods, and dense layers are used to categorize the part of the image since their dropout is 0.2, which prevents them from overfitting and therefore keeping them from doing so throughout the research and model [3].

There were several existing methods and approaches in X-ray body part classification with cross-model comparison few are [4][5]:

1. Convolutional Neural Networks (CNNs): CNNs classify picture, such as by classifying bodily sections from X-ray images. Because they are skilled at learning hierarchical characteristics from images, these deep learning architectures are effective at finding patterns in X-ray scans associated to distinct anatomical parts. Researchers have used a range of CNN architectures, including VGGNet, ResNet, and Inception, to achieve this goal.
2. Transfer Learning: This models are adjusted for a different task using a smaller dataset (e.g., X-ray body part categorization). This can dramatically enhance the performance of the target task even with little data by utilising the information stored in the pre-trained models.
3. Ensemble Methods: To reach a judgement, ensemble methods combine the results of various models' predictions. To modify the overall performance and resilience of the categorization system for X-ray body parts, researchers have used approaches such model averaging, majority voting, and weighted voting.

3. Dataset Description

A significant X-ray dataset is gathered and annotated. Then, we train a collection of cutting-edge. The X-ray body part classification project's methodology entails gathering a sizable dataset of X-ray images and accompanying body part labels. To extract pixel arrays and normalize them to a constant scale, the DICOM pictures undergo pre-processing. We divided the dataset into train, validation, and test sets using a stratified random sampling technique, with the corresponding ratios being 0.7/0.15/0.15. In order to train deep learning algorithms, 11,263 photos will be utilized. Then, 2,411 and 2,419 images will be used as test sets and validation sets, respectively, to assess the algorithms. Each image was then resized to 512 by 512 pixels and saved in the.PNG format.

4. Technologies Used

- Python: The primary programming language used for the project is Python, which is commonly chosen for its ease of use, extensive libraries, and popularity in the DL community.
- Fast AI: It simplifies the process of building and training complex neural network architectures and provides convenient data processing and augmentation functionalities.
- TensorFlow: TensorFlow is another popular deep learning library used in the project. It is known for its

scalability and versatility in building complex neural network models.

- NumPy and Pandas: NumPy and Pandas are essential libraries in the Python data science ecosystem. They are used for data manipulation, handling arrays, and performing various data processing tasks.
- PyDICOM: PyDICOM is a Python library used for reading and working with DICOM files.
- Kornia and OpenCV: These libraries are used for image processing tasks such as resizing, normalization, and handling pixel arrays.
- Matplotlib and Seaborn: Matplotlib and Seaborn are used for data visualization, allowing the project to create graphs and plots for model evaluation and analysis.
- Scikit learn: Scikitlearn, may be used for data splitting, pre-processing, and evaluation metrics during the initial stages of the project.
- Google Collab: Google collab is used as the interactive development environment to run and test the code, as it allows for a combination of code, text, and visualizations.

The following are the objectives of this project:

- Classification of X-ray Body Parts: The main objective is to develop a model that is capable of correctly detecting different body parts in X-ray pictures, such as the hand, ankle, and chest.
- Automated Image Analysis: The system's goal is to eliminate the need for manual intervention by medical experts by automating the process of recognizing body sections in X-ray pictures.
- Effective Diagnosis Support: The initiative aims to help clinicians make quicker and more accurate diagnoses by swiftly and effectively identifying X-ray images.

The project "X-ray Body Part Classification with Cross Model Comparison" is driven by the chance to advance machine learning models, facilitate generalisation, improve healthcare efficiency, support medical diagnostic support, encourage research and development, and increase healthcare access. This project automates the classification of body parts in X-rays and compares various models with the goal of assisting radiologists, streamlining workflow, advancing models, enabling knowledge transfer to other medical imaging tasks, maximizing resource allocation, encouraging research, and providing high-quality healthcare to underserved areas.

The objective of the project is to create a thorough system that can correctly categorize X-ray images into many body parts, including the chest, hand, knee, shoulder, and more. As part of the research, a variety of X-ray picture datasets will be gathered, data preprocessing will be done. This project's scope includes developing and putting into use a DL based system for classifying X-ray body parts. The major goals are to automate image processing, develop a model that can recognize various body components in X-ray images, and help doctors make quicker and more accurate diagnoses. Based on the given dataset, the project is restricted to X-ray images and preset body component classes. Future improvements could include multi-class classification, a bigger, more varied dataset, and real-time interaction with imaging equipment for seamless clinical support. Through automated X-ray body component identification, the ultimate goal is to improve patient care and the diagnostic abilities of medical personnel.

The target labels are set up in a format that is good for training. There are three sets created from the dataset: training, validation, and testing. Using FastAI or TensorFlow, a convolutional neural network (CNN) is created, which is then trained on the training dataset using the proper optimizer and loss function. On the validation and testing sets. By modifying the architecture and the hyperparameters, the model can be adjusted and optimized. The model is used to forecast body components in fresh X-ray pictures after being trained. Future considerations for the project's deployment, such as multi-class classification, dataset expansion, and integration with real-time medical imaging systems, may be included. To guarantee the correctness and dependability of the X-ray body part categorization system, consideration is made throughout the project to the data quality, model performance, and evaluation metrics.

5. Proposed System

The proposed system is an innovative method for classifying distinct body components in X-ray pictures that makes use of deep learning techniques. The technology seeks to give medical personnel effective and automated image analysis help, enabling quicker and more accurate diagnosis.

The key parts of the system are data collection, preprocessing of the data, model construction, training, and evaluation. Gathering an extensive and varied series of X-ray images is the first step, and each image must have labels identifying the bodily part it contains. The photos are altered to guarantee a constant size and to enable data manipulation, pixel values are normalized.

Convolutional neural network (CNN) architecture is shown in fig.1 selected for model development due to its efficiency in picture categorization tasks. The pre-processed dataset will train the CNN, which is created using TensorFlow or FastAI. To reduce errors and boost accuracy, the model's parameters are changed during the training phase using the proper optimizer and loss function.

When the model is being trained on a validation dataset, its performance is monitored to avoid overfitting and determine the best model configuration. After training, the model's performance is evaluated on a different testing dataset to determine how well it can adapt to brand-new, unexplored X-ray pictures.

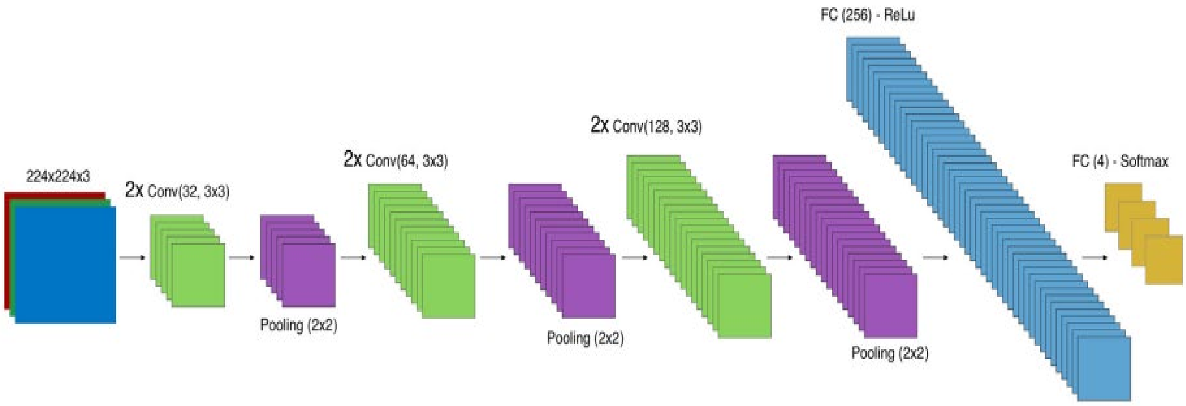

Figure 1. Architecture

The proposed system's key features include:

- Automation: The system eliminates the need for manual medical staff intervention in the process of recognising body sections in X-ray pictures.
- Accuracy: The system uses deep learning to achieve great accuracy in classifying various body parts, producing findings that can be relied on and trusted.
- Real-time Application: The system is built for efficiency and has the potential to make predictions in real time, which makes it useful in situations when timing is crucial.
- Scalability: For seamless clinical support, the suggested system can be expanded to handle enormous datasets and incorporated into already-existing medical imaging systems.
- Interpretability: Before making clinical judgements, medical experts can test and confirm the predictions using the system's output.
- Future Extensions: Multi-class classification that takes into account finer-grained body part characteristics can be added to the system.

5.1 Product Perspective

The X-ray Body Part Classification system with Cross Model Comparison is intended to help medical practitioners classify various body parts quickly and reliably from X-ray pictures. The programme can be used independently or incorporated with the Picture Archiving and Communication Systems (PACS) already in use in medical facilities. An overview of the product perspective is provided below:

Target Users:

Radiologists: The primary users of the system are radiologists and medical imaging specialists who regularly analyze X-ray images to diagnose medical conditions.
Medical Practitioners: Other medical professionals, such as orthopedic surgeons and general practitioners, can also benefit from using the system to aid in their diagnostic processes.

Integration and Compatibility

The system should be designed to integrate seamlessly into existing medical imaging workflows and PACS, allowing for easy adoption and widespread use.
The product should be compatible with a variety of X-ray image formats commonly used in the medical field, ensuring flexibility in data input.

User Interface and User Experience

The user interface should be intuitive, visually appealing, and designed with a focus on user experience. It should be easy to navigate, even for users with limited technical expertise.
The system should provide interactive tools for users to upload, view, and manipulate X-ray images, and access the classification results.

Performance and Accuracy

The primary objective of the product is to achieve high accuracy in both in normal and abnormal cases.
The system should be optimized for efficient processing of X-ray images to provide real-time or near-real-time results, enhancing productivity for medical practitioners.

Cross Model Comparison

One of the unique features of the product is the incorporation of cross model comparison, where multiple deep learning and machine learning architectures are evaluated and compared.
The system should provide clear visualizations and performance metrics, enabling users to make informed decisions about model selection and ensemble strategies.

Interpretability and Transparency

To build trust and enhance the clinical applicability of the system, interpretability tools like Grad-CAM should be included to highlight regions predictions.

The system should provide explanations for its classification decisions to help medical professionals understand and validate the results.

Validation and Medical Approval

The product should undergo rigorous validation with real-world X-ray data, involving collaboration with medical experts to ensure accuracy and reliability.

The system should adhere to relevant medical regulations and standards to obtain necessary approvals for clinical use.

5.2 Product Function

The X-ray Body Part Classification with Cross Model Comparison system offers a range of essential functions designed to provide accurate X-ray image classification and facilitate effective medical diagnosis. Here are the key product functions:

X-ray Image Upload

Users can upload X-ray images to the system through an intuitive and user-friendly interface.

The system should support multiple image formats commonly used in the medical field.

X-ray Body Part Classification

. The system analyses the uploaded X-ray images using DL models and machine learning algorithms to classify different body parts, such as chest, spine, limbs, etc.

It provides real-time or near-real-time classification results, assisting medical professionals in making timely diagnoses.

Cross Model Comparison

. The product incorporates multiple deep learning architectures and machine learning models for the classification task.

The system performs cross model comparison, evaluating the performance of each model and generating relevant performance metrics.

Model Ensemble

. The system employs ensemble techniques to combine predictions from individual models, potentially improving overall classification accuracy and robustness.

Performance Metrics and Visualization

. The product presents performance metrics, including accuracy, precision, recall, F1 score, and area under the receiver operating characteristic curve (AUC-ROC), for each model and ensemble.

Visualizations like graphs and charts are provided to facilitate an easy comparison between different model performances.

6. Implementation

6.1 Pre-processing data

First, we need to convert dicom files to objects that we can use; CSV files, jpg or png images e.g. To do this, we can use pydicom library for reading dicom files and then converting them. Convert some parts of dicom file to pandas dataset. Furthermore, there's another csv file in the main dataset that includes "SOP IDs" and "targets". The labels are represented as integers that map to the following:
Abdomen = 0, Ankle = 1, Cervical Spine = 2, Chest = 3, Clavicles = 4 ,Elbow = 5, Feet = 6, Finger = 7, Forearm = 8, Hand = 9, Hip = 10, Knee = 11, Lower Leg = 12, Lumbar Spine = 13, Others = 14, Pelvis = 15, Shoulder = 16, Sinus = 17, Skull = 18, Thigh = 19, Thoracic Spine = 20 ,Wrist = 21

As you see, some of dicom files have more that one class (target)So, we have a multilabel classification problem. First we add all labels to the "train_df" as new columns by their orders and set all to zero. Then by considering the numbers in the target column of each record, we replace 1 in the columns related that number.

For example, suppose that target has two numbers: "1 , 6". These numbers represent "ankle, feet". We replace 1 in "ankle" and "feet" columns of that record. Merge two dataframs based on "SOPInstanceUID" columns. So we have an integrated dataframe which help us to create "X" and "y" of model much easier. An example of converting dicom file to jpg image. This step is the most time-consuming part of the code.

First, we should reading dicom files and convert them to jpg images but there is a big problem; The size of dicom images are too big; for example 3000 * 4000 pixels! There isn't enough memory so we should resize all of them to 128 * 128 pixels but unfortunately it will have consequences like information loss. If you have enough memory, you can resize them to 512 * 512 pixels for example. Anyway, the images create X array for training.

The “y” of model is an array of 1738 * 22. In another words, the label of each image (each SOPInstanceUID) is a vector contains 22 binary numbers that represent 22 labels (body parts).

6.2 Training and testing our custom CNN model

First, we should split X and y data to train and test data. To avoid overfitting, we can use "EarlyStopping" callback; So, need to split train data to "train" and "validation" parts. Now, we can build our CNN model.

Plotting results of trained model involves accuracy and loss. During Prediction, first select a dicom file from test data and convert it to jpg image same as training phase. Then pass it to "predict" function and get output. After some tests, I set threshold = 0.1 which means if score is greater than 0.1, the related label is in that test image.

7. Result Analysis

Figure 2. shows how well our model is able to make correct predictions on both the trained and tested data over each epoch. The object contains the training history of the model, including the accuracy for each epoch. Creates a subplot with two panels, Y one for the accuracy and X one for the epoch. Plots the accuracy for each epoch in the respective panel.

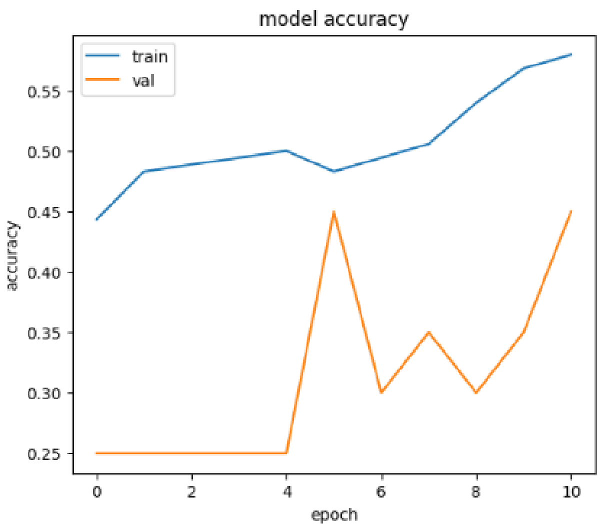

Figure 2. Model Accuracy

Figure 3. shows how well our model is minimizing its lost function on both the trained and tested data over each epoch. The history object contains the training history of the model, including the loss for each epoch. The code first creates a subplot with two panels, Y one for the loss and one X for the epoch. The table.1 shows the accuracy and loss respective to each epoch. Accuracy and loss are often used together to evaluate the performance of a machine learning model. A model with high accuracy and low loss is considered to be a good model.

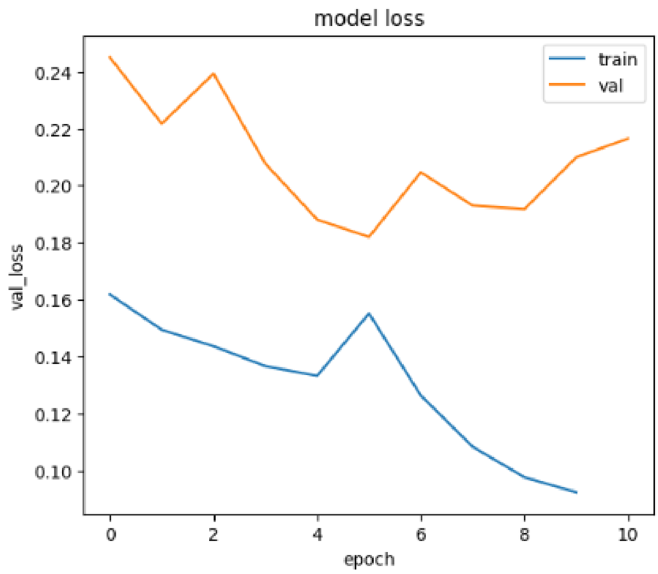

Figure 3. Model loss

Table 1. Accuracy and loss

Epoch(E)	Steps	Training-Loss	Training-Accuracy	Validation-Loss	Validation-Accuracy
E-1	22	0.8043	0.4432	0.2450	0.2500
E-2	22	0.1618	0.4830	0.2217	0.2500
E-3	22	0.1494	0.4886	0.2393	0.2500
E-4	22	0.1436	0.4943	0.2077	0.2500
E-5	22	0.1366	0.5000	0.1881	0.2500
E-6	22	0.1332	0.4830	0.1819	0.4500
E-7	22	0.1551	0.4943	0.2046	0.3000
E-8	22	0.1263	0.5057	0.1930	0.3500
E-9	22	0.1083	0.5398	0.1917	0.3000
E-10	22	0.0976	0.5682	0.2099	0.3500
E-11	22	0.0923	0.5795	0.2165	0.4500

The fig.4 shows the model has identified the image of an x-ray as feet, where the image was processed, and the size of its pixels was converted and displayed in a grayscale. Fig.5 shows the model has identified the image of an x-ray as chest, where the image was processed, and the size of its pixels was converted and displayed in a grayscale. Fig.6 shows the model has identified the image of an x-ray as chest, where the image was processed, and the size of its pixels was converted and displayed in a grayscale. Fig.7 shows the model has identified the image of an x-ray as abdomen, where the image was processed, and the size of its pixels was converted and displayed in a grayscale.

Figure 4. Model loss X-ray identified as of feet.

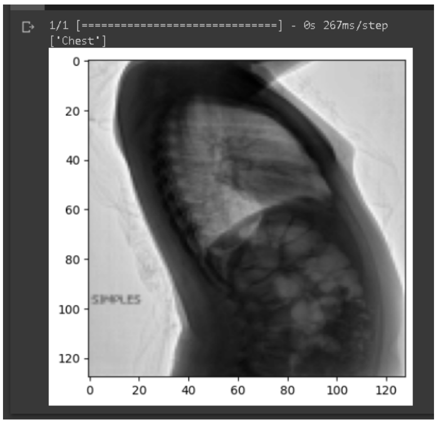

Figure 5. Side Chest

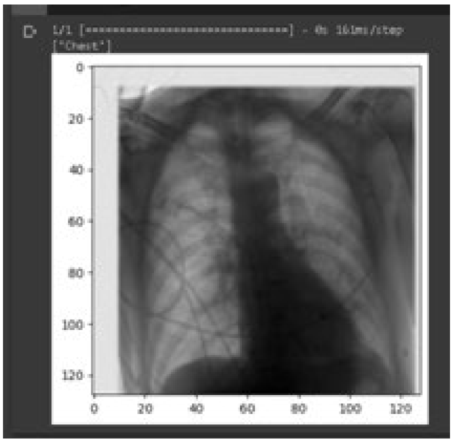

Figure 6. Chest

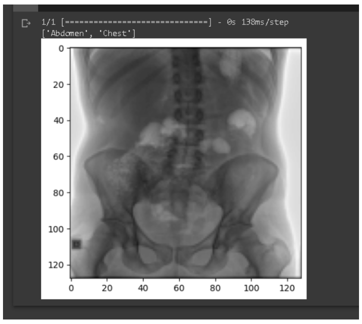

Figure 7. Abdomen.

Figure 8. Wrist

Fig.8 shows the model has identified the image of an x-ray as wrist, where the image was processed, and the size of its pixels was converted and displayed in a grayscale. The table.2 shows the comparison table of CNN with wavelet (WF), Texture (TF) and HoG(HF) features. CNN shows 97.38% performance.

Table.2 Comparison with different Classifiers and CNN

Class	WF	TF	HF	CNNs
Cl-1	96	75	99	97
Cl-2	96	63	83	97
Cl-3	99	55	99	100
Cl-4	99	79	95	97
Cl-5	95	15	99	97
Cl-6	99	67	83	97
Cl-7	91	27	87	97
Cl-8	91	79	91	97
Av	95.75	57.5	92	97.38

8. Conclusion

In conclusion, the future prospects for the X-ray Body Part Classification using Custom CNN Comparison system are extensive. There is a vast scope for further enhancements in model architectures, seamless integration with other imaging modalities, and the refinement of interpretability and real-time implementation. The study demonstrates the effective Convolutional Neural Networks in automating the classification of body parts in X-ray pictures, with a focus on accuracy, loss reduction, and real-time applicability. These anticipated developments hold the promise of creating a significantly more efficient, accurate, and adaptable tool for medical professionals. Ultimately, this technological advancement stands to greatly enhance patient care and facilitate more informed and precise medical decision-making.

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