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SIGN LANGUAGE PREDICITION USING CNN

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INTRODUCTION

A human body consists of 206 bones. Bones are attached to the muscle of the body and provide support for the movements. Bone ligaments are fibrous tissue and filled with spongy bone marrow. A bone cancer originates from the healthy cells and starts forming a tumor. The primary symptom of bone cancer is a bone tumor. The tumor grows gradually and may spread to the other part of the body. It can destroy the bone tissue and bone becomes weaker. According to statics, 3500 people in the United State were affected by bone cancer in the year 2018, and approx. 47% of the bone-cancer diagnosed people died. The doctor diagnoses cancer via many tests. The X-ray image diagnosis is used to detect cancer in the human bone. The healthy bone and the cancerous bone X-ray assimilation rates are different. Due to which a cancerous bone image surface appears ragged. The bone cancer severity is measured by a stage and the grade. Tumor growth rate is used by doctors to
predict the disease growth rate. Diagnosing cancer in the bone requires expertise. Bone cancer diagnoses are of cancer-affected patients. Deals with the system which uses the Deep learning algorithm CNN and image processing techniques to detect the tumor and classify cancer.

1.2 NEED FOR THE PROJECT

Bone cancer is considered a serious health problem, and, in many cases, it causes patient death. The X-ray, MRI, or CT-scan image is used by doctors to identify bone cancer. The manual process is time-consuming and required expertise in that field. Therefore, it is necessary to develop an automated system to classify and identify the cancerous bone and the healthy bone. The texture of a cancer bone is different compared to a healthy bone in the affected region. But in the dataset, several images of cancer and healthy bone are having similar morphological characteristics. This makes it difficult to categorize them. To tackle this problem, we first find the best suitable edge detection algorithm after that two feature sets one with Bone Cancer and another without Bone Cancer are prepared.
Bone cancer is a type of cancer that Benin's in the bones and can spread to other parts of the body. Early detection and accurate diagnosis of bone cancer are critical for effective treatment and improved patient outcomes. However, the diagnosis of bone cancer can be challenging, as it often requires the interpretation of complex imaging data.
Convolutional neural networks (CNNs) are a type of artificial neural network that have been shown to be effective in image recognition tasks, including medical image analysis. By leveraging CNN algorithms, it may be possible to develop automated systems that can accurately detect and diagnose bone cancer from medical imaging data.

1.3 OBJECTIVES OF THE PROJECT

The main objective of using the Convolutional Neural Network (CNN) algorithm in the detection of bone cancer is to improve the accuracy and efficiency of the diagnosis process. Specifically, some of the objectives of using CNN in the detection of bone cancer. One of the primary objectives of using CNN in the detection of bone cancer is to detect the disease at an early stage. Early detection is critical in the successful treatment of bone cancer and can significantly improve the chances of recovery.

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Another objective of using CNN in the detection of bone cancer is to improve the accuracy of diagnosis. CNN can help to accurately identify the location and extent of the tumor, which is crucial in determining the appropriate treatment approach. Efficiency: CNN can also help to improve the efficiency of the diagnosis process. With the use of CNN, radiologists can quickly and accurately analyze large volumes of medical images, leading to faster and more effective diagnosis.
In the project have the used to based on Classification and Detection of Bone Cancer using a deep learning. Three-layered convolutional deep-learning architecture is used for the pre-processing, feature extraction and max pooling layer. An individual's identity is ascertained using these three layers.

1.4 PROJECT DESCRIPTION

This project 'Deep learning based Classification and Detection of Bone Cancer' is the X-ray image diagnosis is used to detect cancer in the human bone. The healthy bone and the cancerous bone X-ray assimilation rates are different. Due to which a cancerous bone image surface appears ragged. The bone cancer severity is measured by a stage and the grade.

SYSTEM ANALYSIS

2.1 INTRODUCTION

Design is the first step in the development phase for any techniques and principles for the purpose of defining a device, a process or system in sufficient detail to permit its physical realization. Once the software requirement have been analyzed and specified the software design involving three technical activities-design, coding, implementation and testing that are required to build and verify the software.

2.2 SYSTEM STUDY

The specific details of the project are specified by the Classification and Detection of Bone Cancer. In this document, various steps involved in the existing system process have been explained.

2.3 EXISTING SYSTEM

For do this project in existing system we have threshold process to detect the cancer part. The process is we are taking the input image as MRI and CT images of symptoms of neoplasm. After that according to our requirement we are interchanging the pixel values, means converting and resizing the image. By using some filters we are reducing the noise. Here detecting the cancer part is more difficult to do this we are using K-NN algorithm. We are using the threshold process (figure 2.3) to clear the structure of the input image. Afterwards we need to cluster the part to detect what type of cancer it was. Here we are not using any particular algorithm for clustering manually we are analyzing the process. But it is very difficult to do the process.

The drawbacks of existing system we have. It is difficult to get the accurate results By using these techniques. If we applied multiple images at a time, we can't get the results very soon. It consumption more time to give the results. In medical images by default itself we have some noise, it is very difficult to filter and classify. It may give inaccuracy classification is shown in figure 2.3.

2.3.1 Drawbacks of Existing System

- Image segmentation techniques can be applied on Bone X-Ray or MRI image to recognize an unwanted growth of bone which may be Benign (not cancer) or Malignant.
- Low efficiency
- Detection very

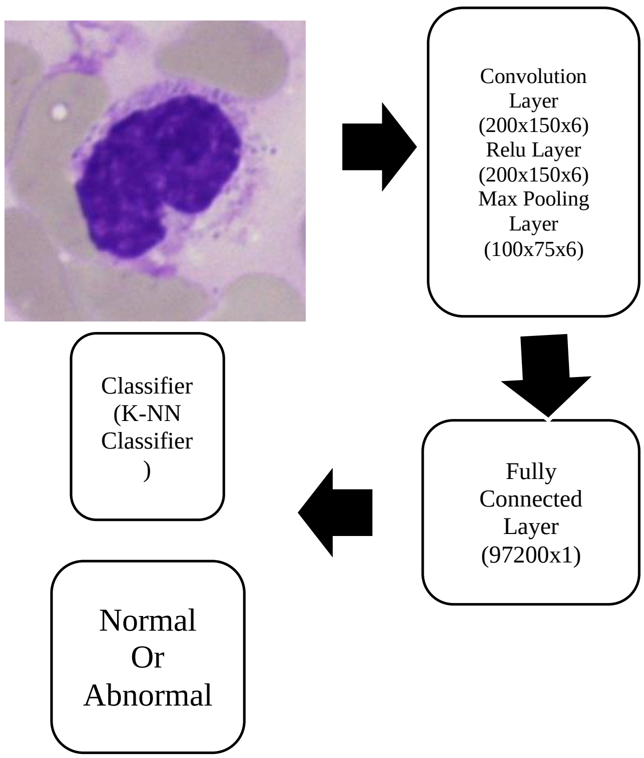

Figure 2.3 Existing System

2.4 PROPOSED SYSTEM

- Discrete Wavelet Transform(DWT)
- Gray level co-occurrence(GLCM) Feature Extraction
- Convolutional Neural Network (CNN) Training and Classification
- The logical module of the proposed method using CNN classifier. It consists of training and testing stage. CNN is applied which includes mainly convolution layer, Relu layer and Max pooling layer.

2.5 MODULE DESCRIPTION

'Classification and Detection of Bone Cancer' includes a Processing of project is Show in figure 2.5

The project includes five processing modules, they are:

1. Input Data Set
2. Image Pre-Processing
3. Segmentation process
4. Classification
5. Report

Convolution Layer
(50x37x216)
Relu Layer
(50x37x216)
Max Pooling Layer
(25x18x216)

2.5.1 Input Data Set

The Data entry involves receiving the data of MRI and CT images from the user and sending them for Pre-Processing. This input data set is downloaded from the Kaggle website.

2.5.2 Image Pre-Process

Image pre-processing is the term for operations on images at the lowest level of abstraction. The aim of pre-processing is an improvement of the image data. Remove the undesired background image.

2.5.3 Segmentation Process

DWT used to detect the cancer in bone (MRI) and (CT) images. The both algorithms is used to segment the cancer from bone and lung images. The image can be segmented thoroughly and finally obtained the image into segments.

2.5.4 Classification

Normally the classification is used to classify that the image is normal or abnormal. CNN is one type of classifier, the features and values of the cancer affected image and non cancer image is already placed in database, the intensity is also having in cancer affected image, the classifier compares the given image within the database if the cancer is identified while comparing the each pixels, it display the message box the cancer is affected, after completing the CNN training.

2.5.5 Report

Finally, can detect authentication Normal and Abnormal.

SYSTEM DESIGN AND DEVELOPMENT

The system analysis follows system designs with two major aspects namely are;

i) Logical design
ii) Physical design.

Following the design, the development of the system based on coding design using the chosen software technologies is carried out.

3.2 LOGICAL DESIGN

The logic design of the system is conceived and represented using some standard design elements such as algorithmic procedures, Flowcharts System Flow diagram, Data Flow Diagram.

Use Case Diagram

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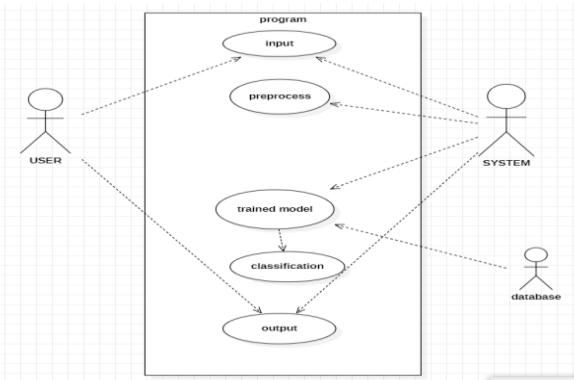

Figure 3.2 Use Case Diagram

Show in Figure 3.2 Describes the case diagram can be organizing and planning the project, identifying stakeholders, communicating and collaborating with team members, and

3.3 PHYSICAL DESIGN

The physical design is the actual design of data set design.

3.3.1 Data Set Design

Database design is the process of producing a detailed data model of a database. This Data store the Bone image in your database you will need to set up storage item, an identical process to how you store a photo and collected data set from the online website. The JPG file is used by many editing programs and software is Show in table 3.3

This dataset was obtained from online (http://www.Kaggle.com).

TABLE 3.3 Dataset image format table

S. NO.	IMAGE NUMBER	TYPE	SIZE
1	EBO_00001	JPG File	322 KB
2	EBO_00002	JPG File	395 KB
3	EBO_00003	JPG File	2,813 KB
4	EBO_00004	JPG File	316 KB
5	EBO_00005	JPG File	266 KB
6	EBO_00006	JPG File	327 KB
7	EBO_00007	JPG File	282 KB
8	EBO_00008	JPG File	248 KB
9	EBO_00009	JPG File	372 KB
10	EBO_00010	JPG File	2,073 KB
11	EBO_00011	JPG File	422 KB
12	EBO_00012	JPG File	1,192 KB
13	EBO_00013	JPG File	338 KB
14	EBO_00014	JPG File	242 KB
15	EBO_00015	JPG File	323 KB
16	EBO_00016	JPG File	254 KB
17	EBO_00017	JPG File	342 KB
18	EBO_00018	JPG File	1,271 KB
19	EBO_00019	JPG File	286 KB

20	EBO_00020	JPG File	3,258 KB
21	EBO_00021	JPG File	1,295 KB
22	EBO_00022	JPG File	926 KB
23	EBO_00023	JPG File	193 KB
24	EBO_00024	JPG File	322 KB
25	EBO_00025	JPG File	778 KB
26	EBO_00026	JPG File	226 KB
27	EBO_00027	JPG File	215 KB
28	EBO_00028	JPG File	299 KB
29	EBO_00029	JPG File	1,155 KB
32	EBO_00032	JPG File	169 KB
31	EBO_00031	JPG File	3,196 KB
32	EBO_00032	JPG File	1,313 KB
33	EBO_00033	JPG File	2,132 KB
34	EBO_00034	JPG File	1,691 KB
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36	EBO_00036	JPG File	1,199 KB
37	EBO_00037	JPG File	1,031 KB
38	EBO_00038	JPG File	324 KB
39	EBO_00039	JPG File	1,764 KB
40	EBO_00040	JPG File	355 KB
41	EBO_00041	JPG File	2,349 KB
42	EBO_00042	JPG File	1,127 KB
43	EBO_00043	JPG File	277 KB
44	EBO_00044	JPG File	1,649 KB
45	EBO_00045	JPG File	876 KB
46	EBO_00046	JPG File	182 KB
47	EBO_00047	JPG File	1,080 KB
48	EBO_00048	JPG File	320 KB
49	EBO_00049	JPG File	1,332 KB
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54	EBO_00054	JPG File	1,066 KB
55	EBO_00055	JPG File	175 KB
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57	EBO_00057	JPG File	254 KB
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72	EBO_00072	JPG File	2,349 KB
73	EBO_00073	JPG File	1,127 KB
74	EBO_00074	JPG File	277 KB
75	EBO_00075	JPG File	1,649 KB
76	EBO_00076	JPG File	876 KB
77	EBO_00077	JPG File	182 KB
78	EBO_00078	JPG File	1,080 KB
79	EBO_00079	JPG File	320 KB
H680	EBO_00080	JPG File	1,332 KB
81	EBO_00081	JPG File	1,325 KB
82	EBO_00082	JPG File	3,454 KB
83	EBO_00083	JPG File	3,639 KB
84	EBO_00084	JPG File	1,763 KB
85	EBO_00085	JPG File	1,066 KB
86	EBO_00086	JPG File	175 KB
87	EBO_00087	JPG File	294 KB
88	EBO_00088	JPG File	254 KB
89	EBO_00089	JPG File	570 KB
90	EBO_00090	JPG File	288 KB

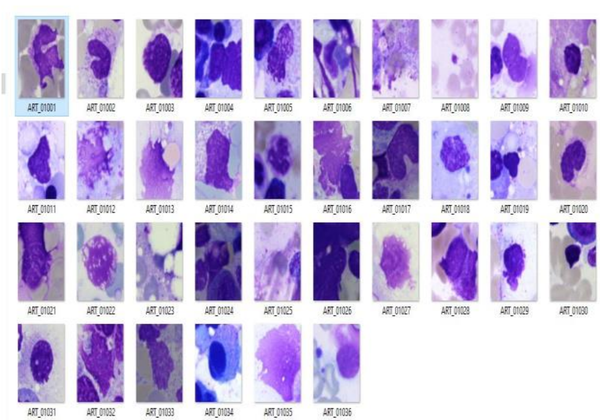

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Figure 3.3 Dataset

3.4 MODULE DESCRIPTION

'Classification and Detection of Bone Cancer' includes a Processing of project is Show in Figure 3.4

The project includes five processing modules, they are:

1. Input Data Set
2. Image Pre-Processing
3. Segmentation process
4. Classification
5. Figure 3.6 Processing of Project

3.4.1 Input Data Set

To Store the Bone image in your database you will need to Set up a storage item, an identical process to how you store a photo. The input image is in (DICOM) format this image can be convert into JPEG format and resize the image, because the image is having more size, it requires more time for segmentation process and less picture quality. So the size should be resized into 256*256. The input images for this work using Bone images received from User.

3.4.2 Image Pre-Process

Preprocessing is used to improve the quality of an image. Every image has contained some salt and pepper noise having some blurriness. To remove the noise and blurriness. Image pre-processing is the term for operations on images at the lowest level of abstraction. The aim of pre-processing is an improvement of the image data. Remove the undesired background image. Extracting the bone tumor Part. Pre-processing return the best result and used to further analysis.

3.4.3 Segmentation Process

DWT used to detect the cancer in bone (MRI) and (CT) images. The both algorithms is used to segment the cancer from bone and lung images. The image

can be segmented thoroughly and finally obtained the image into segments.

3.4.4 Classification

Normally the classification is used to classify that the image is normal or abnormal. CNN is one type of classifier, the features and values of the cancer affected image and non cancer image is already placed in database, the intensity is also having in cancer affected image, the classifier compares the given image within the database if the cancer is identified while comparing the each pixels, it display the message box the cancer is affected, after completing the CNN training.

Classification Process is Show in figure A1.8

3.4.5 Report

Finally can detect authentication Normal and Abnormal.

TESTING & IMPLEMENTATION

4.1 INTRODUCTION

Software testing is a critical element of software quality assurance and represents the ultimate review of specification, design and code generation. At the time of developing the code and executing the code, he lists of errors are identified (both syntax and semantic) and corrected. After the system designed, code is written, there is usually a procedure in place for testing the system for bugs, performance and reliability.

4.2 Software Testing

System testing tests the system as a whole. Once all the components are integrated, the application as a whole is tested rigorously to see that it meet the specified Quality Standards. This type of testing is performed by a specialized testing team. System testing is important because of the following reasons: System testing is the first step in the Software Development Life Cycle, where the application is tested as a whole.

4.2.1 Unit Testing

Unit testing verification efforts on the smallest unit of software design, module. This is known as "Module Testing". The modules are tested separately. This testing is carried out during programming stage itsel2f. In these testing steps, each module is found to be working satisfactorily as regard to the expected output from the module.

SYSTEM IMPLEMENTATION

In the project have the used to based on bone cancer detection using a deep learning. Three layered convolutional deep-learning architecture is used for the pre-processing, feature extraction and max pooling layer. An individual's identity is ascertained using these three layers.

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4.3.1 Convolution Neural Network

CNN is inspired by the biological phenomenon of the animal visual cortex, which shows the connectivity pattern between different neurons. While using CNN, slight preprocessing is vital, like enhancement or filtering of an image, which is also essential in traditional handmade feature extraction techniques. CNN has a wide range of applications such as image processing, video processing, speech processing, and natural language processing. CNN consists of four significant steps, such as convolution layer, rectified linear unit (Relu), maximum pooling layer, and fully connected layer.

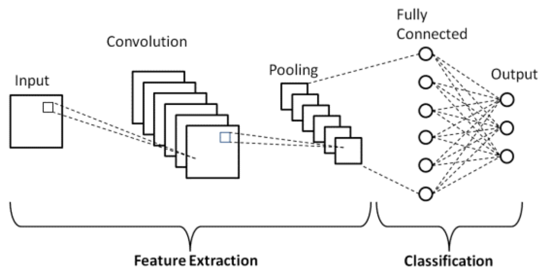

Figure 4.1 CNN Architecture

4.3.2 RELU LAYER

ReLU, short for Rectified Linear Unit, is an activation function commonly used in neural networks, including Convolutional Neural Networks (CNNs). The ReLU layer is a type of activation layer that applies the ReLU function to the input. The ReLU function is defined as f(x) = max(0, x) , which means that it outputs the input value if it is positive, and outputs zero if it is negative. This simple non-linearity has several advantages in neural networks. Since the ReLU function outputs zero for negative inputs, it encourages sparsity in the activations of the neurons. This can lead to more efficient use of parameters and faster training.

Non-saturation: Unlike some other activation functions, the ReLU function does not saturate (i.e., it does not become insensitive to changes in the input). This can help to prevent the problem of vanishing gradients, which can occur when the gradients of the activation function become too small to affect the weights of the network.
Computational efficiency: The ReLU function is computationally efficient to calculate, as it simply involves taking the maximum of two values. In a CNN, ReLU layers are typically added after the convolutional layers to introduce non-linearity and sparsity in the activations. They can also be added after the fully connected layers in the network.
In the convolution layer, an image is multiplied by filter kernel, which may have some negative values. These negative values bring the non-linearity in the image. The non-linearity is then removed by using the rectified linear unit layer by converting all the negative values to zero using where, Relu is the Relu layer image and Icon is the convolutional layer image. The Relu layer (figure 4.2.2) output size is 200×200X3, which is equal to the size of the convolution layer output. The output of the Relu layer is given to max pooling layer is show in figure 4.3

Overall, the ReLU layer is a simple but effective component of a CNN that can improve the performance and efficiency of the network.

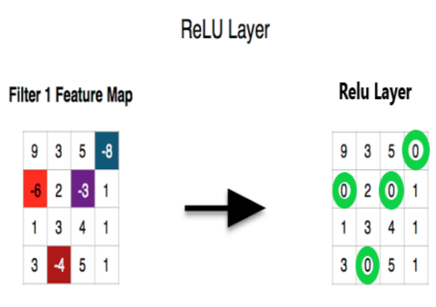

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Figure 4.2 Relu Layer Processing

4.3.3 Max Pooling Layer

Pooling is used for the minimization of the computing cost by reducing the dimension of the Relu layer output is Show in figure 4.2 Pooling is also used to retain the position and rotational invariant features of an image. There are two types of pooling methods: Maximum and Average pooling. In maximum pooling, the maximum value of the given window is selected, while in average pooling, the average value of the window is selected. Unlike average pooling, maximum pooling suppresses the noise in the image along with feature reduction. Pooling is also used to maintain the localization of the shape of the local object in the image. The window size of 2×2 is selected for maximum pooling, which reduced the size to exactly half of the Relu layer (100×75×6). The larger window size for the maximum pooling may result in the fine local information of the image.

Max pooling has several benefits in CNNs: It reduces the spatial dimensionality of the feature maps, which helps to reduce the number of parameters in the network and reduce the risk of over fitting. It helps to increase the translation invariance of the network by allowing the network to recognize the same feature regardless of its position in the input image. It helps to retain the most important features in the input feature map, as the max pooling operation selects the most important values from each region. Overall, max pooling is a powerful tool in CNNs that helps to reduce the spatial dimensionality of feature maps while retaining the most important features, leading to more efficient and effective learning. Max Pooling layer Processing is show in Figure 4.3

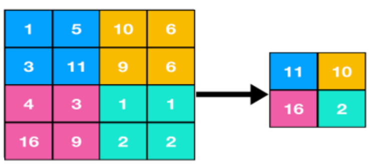

Figure 4.3 Max Pooling Layer
4.3.4 Result & Discussion

The output of the first convolution layer after the convolution of the original image of size 200×200 with the 3×3 filer kernel resulted in two different feature maps. The output of the Relu layer of the first CNN has the same dimension as that of a convolution layer output, but the Relu layer output map has only positive values. All the negative neurons are neglected to remove the non-linearity. The output of the maximum pooling layer is sampled down to exactly half of the original image size, which reduces the dimensions of the feature map. The output of the first CNN layer is again convolved with the filter kernel of size 3×3, which is given to the Relu layer for rectification. After the max-pooling of the second layer of CNN, the feature map has the 100x100x9 dimension. The second layer of CNN generates 36 interconnected maps of the image. Output of CNN layer 2 is given to CNN layer 3, which is further convolved with the learned filter kernel of size 3×3. After rectification, the feature map is given to the max-pooling layer, which further halves subsample for the image maps. The feature map size of the CNN layer three is 13x13x243. The third layer of CNN generates the 243 interconnected maps of the image. As the number of filters increases, the connectivity showing discrimination between the different parts of the image increases. Image Training Accuracy and Training Loss Process is Show in table 4.4

Table 4.4 CNN Processing

DEEP LEARNING LAYER	SUB- LAYER	FEATURE MAP SIZE
CNN Layer-I	Convolution Layer	200x200
	Relu Layer	200x200x3
	Max Pooling Layer	100x100x3
CNN Layer-II	Convolution Layer	100x100x9
	Relu Layer	100x100x9

	Max Pooling Layer	50x50x9

CNN Layer-III	Convolution Layer Relu Layer Max Pooling Layer	50x50x27 50x50x27 25x25x27
CNN Layer-IV	Convolution Layer Relu Layer Max Pooling Layer	25x25x81 25x25x81 13x13x81
CNN Layer-V	Convolution Layer Relu Layer Max Pooling Layer	25x25x243 25x25x243 13x13x243
Fully Connected Layer		41067x1

The system is implemented using computer vision and image processing toolbox of Jupiter on Windows environment. The performance of the system is evaluated based on percentage cross validation accuracy. Show in Table 4.5

Table 4.5 Training Accuracy & Loss

Training Data (Epoch)	**Training Period**	**Epoch Time**	
		Accuracy	**Loss**
1/32	14 Seconds	0.3684	0.8862
2/32	8 Seconds	0.1842	0.1966
3/32	11 Seconds	0.0255	0.0246
4/32	8 Seconds	0.0798	0.1102
5/32	8 Seconds	0.0263	0.1319
6/32	8 Seconds	0.0433	0.0258
7/32	10 Seconds	0.0378	0.0545
8/32	7 Seconds	0.0149	0.0112
9/32	7 Seconds	0.0527	0.0007
10/32	8 Seconds	0.0026	0.0112
11/32	6 Seconds	0.0264	0.0007
12/32	9 Seconds	0.0008	0.0009
13/32	7 Seconds	0.0272	0.0491
14/32	7 Seconds	0.0263	0.0325
15/32	8 Seconds	0.0263	0.0328
16/32	7 Seconds	0.1053	0.0483
17/32	9 Seconds	0.0938	0.0367
18/32	9 Seconds	0.0468	0.0222
19/32	10 Seconds	0.0312	0.0159
20/32	8 Seconds	0.0468	0.0546
21/32	10 Seconds	0.0626	0.0538

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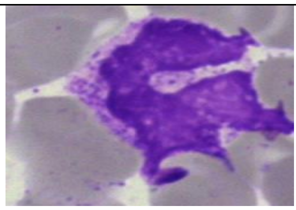
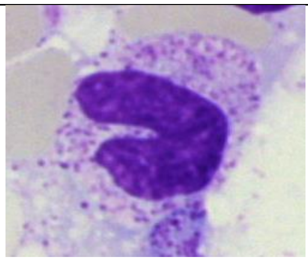
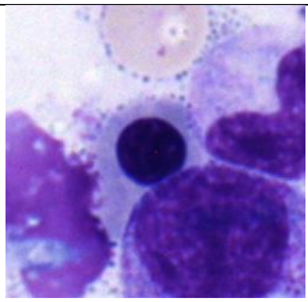
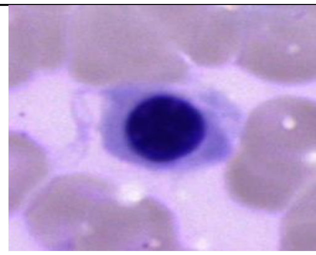
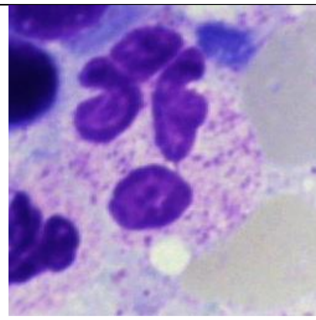
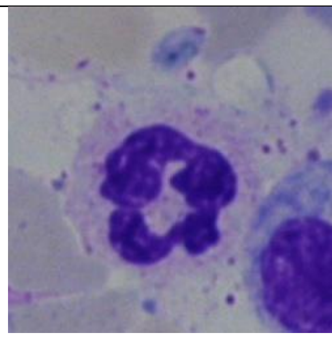
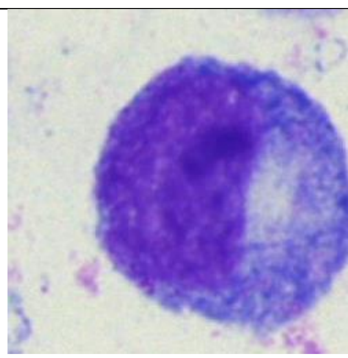
22/32	9 Seconds	0.0312	0.0578
23/32	6 Seconds	0.0132	0.0279
24/32	9 Seconds	0.0107	0.0743
25/32	10 Seconds	0.0125	0.0992
26/32	10 Seconds	0.0312	0.0168
27/32	7 Seconds	0.0658	0.0156
28/32	7 Seconds	0.1582	0.0343
29/32	10 Seconds	0.1859	0.0679
32/32	5 Seconds	0.0509	0.0295
31/32	7 Seconds	0.0345	0.0212
32/32	5 Seconds	0.7234	0.0123

Report: Finally the project ‘Classification and detection of Bone cancer’ will detect Cancer Stage and Print Benign, Normal and Malignant is show in Table 4.6

Table 4.6 Report of Classification and detection of Bone Cancer

S.NO	**Image Name**	**Image**	**Size**	**Result**
1	EBO_00001		432kb	Normal
2	EBO_00075		326kb	Benign
3	EBO_00002		256kb	Malignant

4	EBO_00004		**465**Kb	Benign
5	EBO_00006		**245kb**	Normal
6	EBO_00005		**300kb**	Malignant
7	EBO_00014		423kb	Normal

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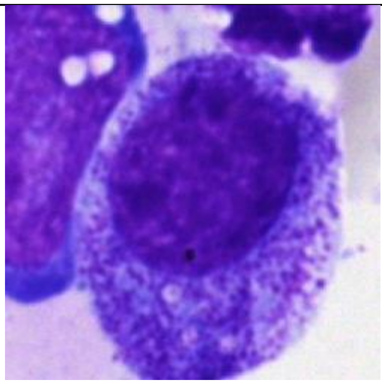
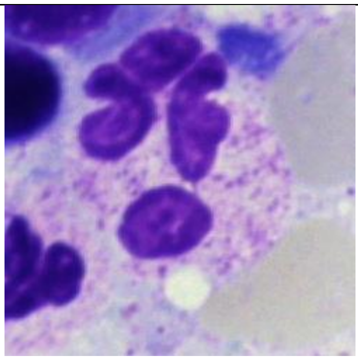
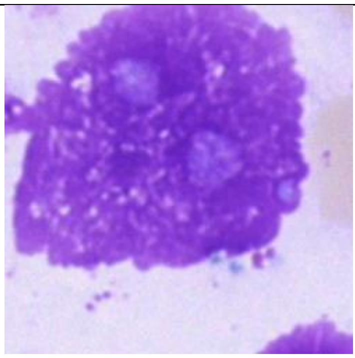
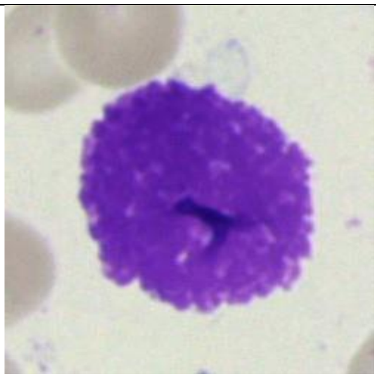
8	EBO_00007		578kb	Benign
9	EBO_00013		432Kb	Malignant
10	EBO_00012		421Kb	Normal
11	EBO_00032		321kb	Benign

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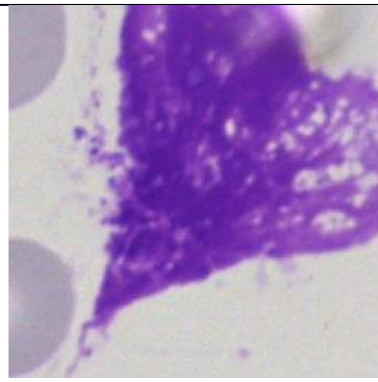
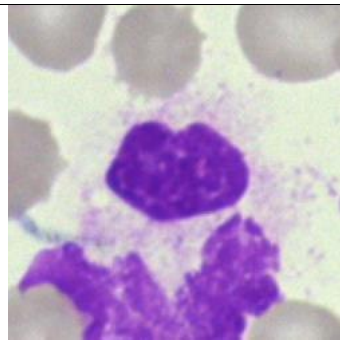
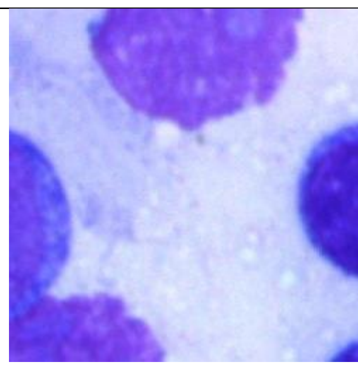
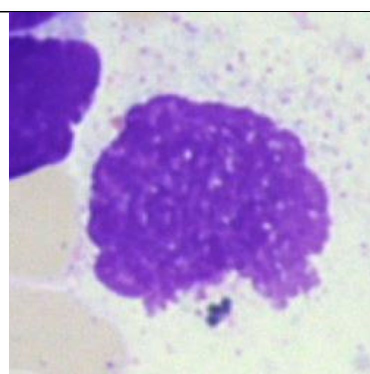
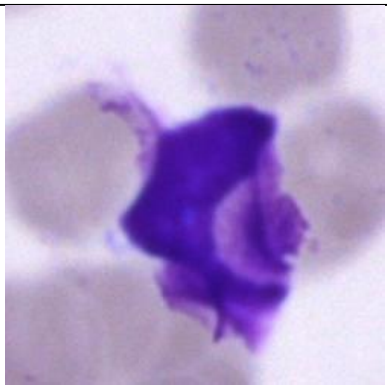
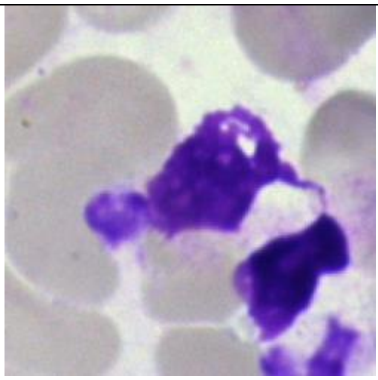
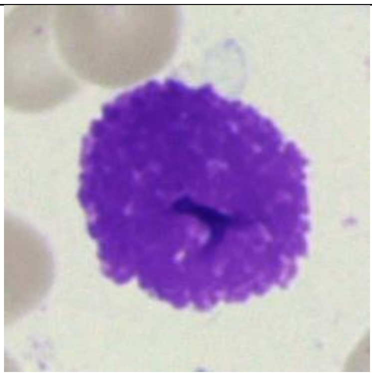
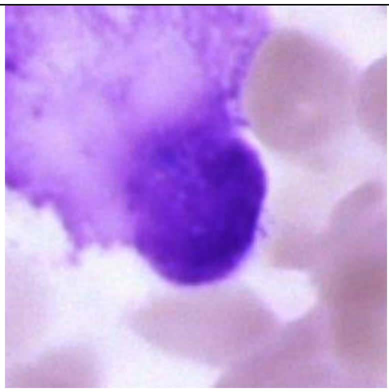
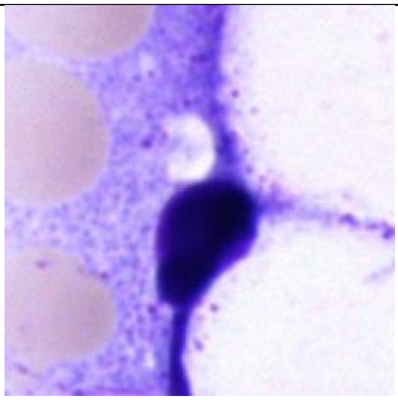
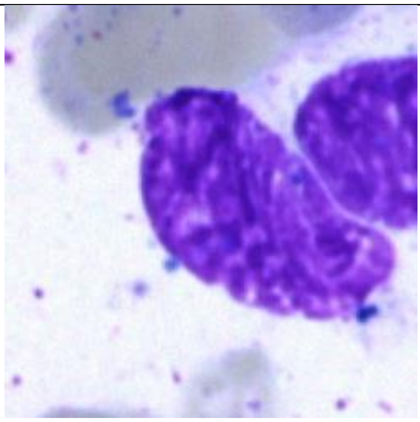
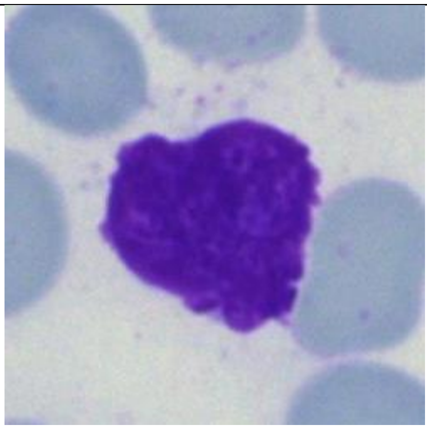
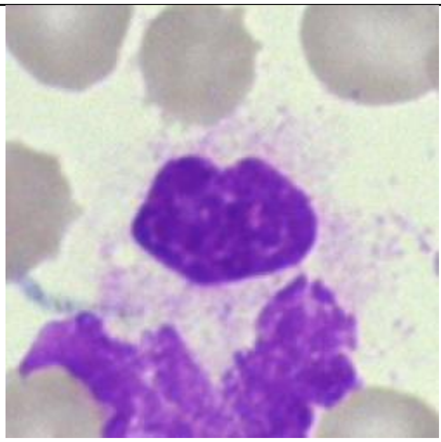
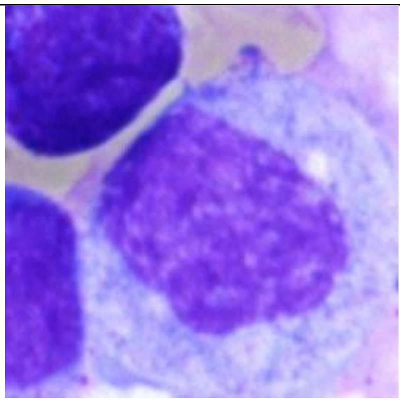
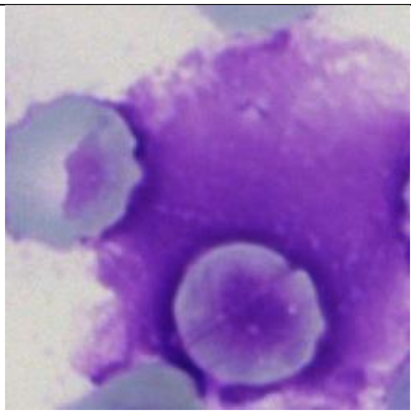
12	EBO_00012		328kb	Malignant
13	EBO_00011		444KB	Normal
14	EBO_00015		666KB	Benign
15	EBO_00010		501KB	Malignant

16	EBO_00016		522KB	Normal
17	EBO_00032		600KB	Malignant
18	EBO_00018		500KB	Normal
19	EBO_00007		522KB	Benign

20	EBO_0009		432KB	Malignant
21	EBO_00017		511KB	Normal
22	EBO_00018		522KB	Malignant

23	EBO_00021		423KB	Benign
24	EBO_00022		488KB	Malignant
25	EBO_00019		545KB	Normal

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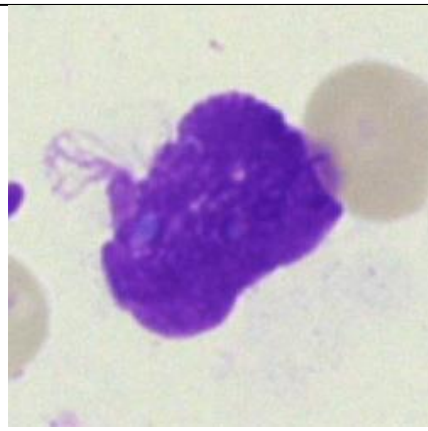
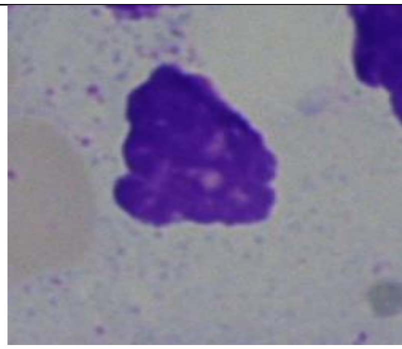
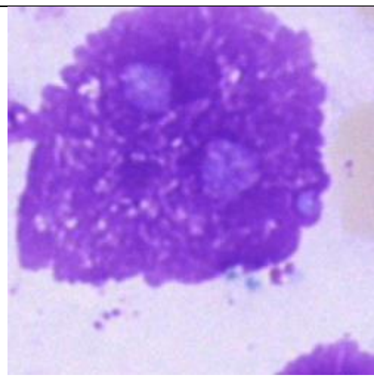
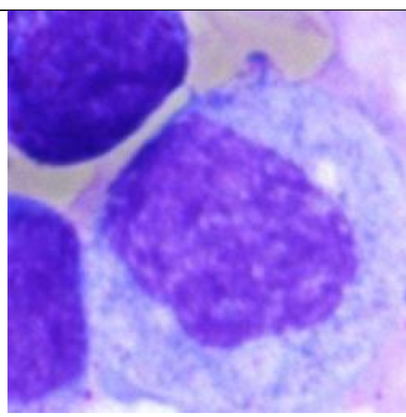
26	EBO_00021		502KB	Benign
27	EBO_00025		555KB	Malignant
28	EBO_00030		611KB	Normal
29	EBO_00028		600KB	Benign

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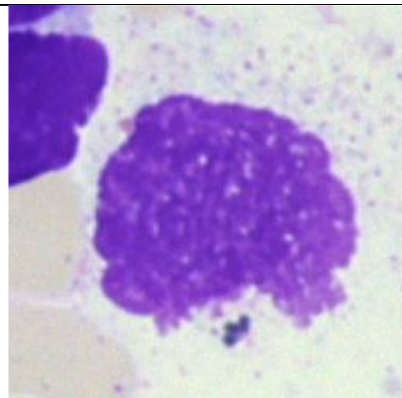
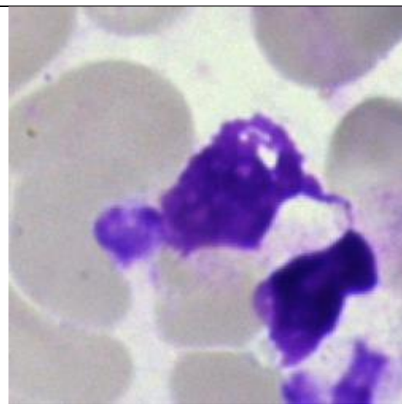
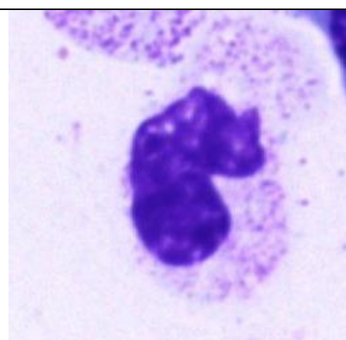
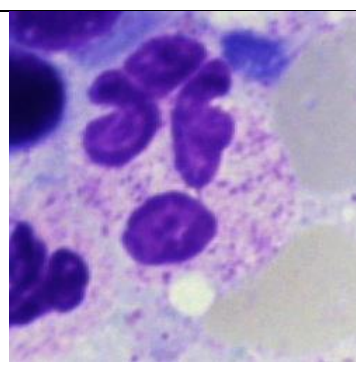
30	EBO_00026		622KB	Malignant
31	EBO_00032		700KB	Normal
32	EBO_00031		425KB	Normal
33	EBO_00032		432Kb	Malignant

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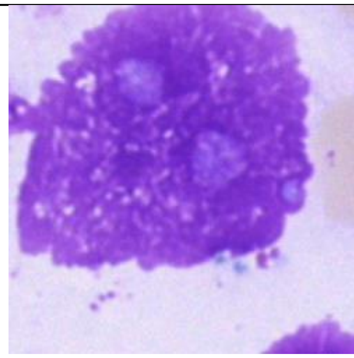
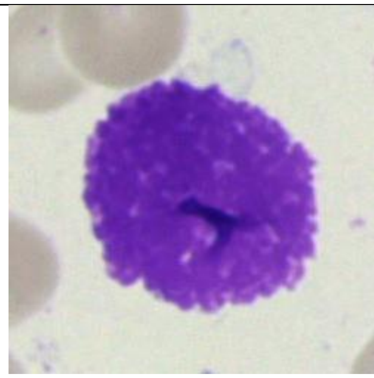
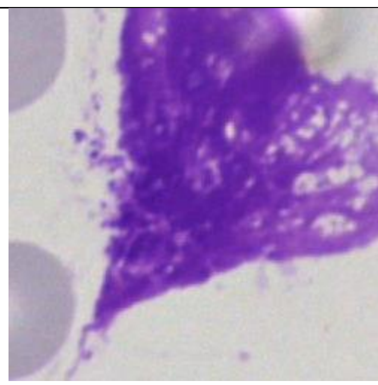
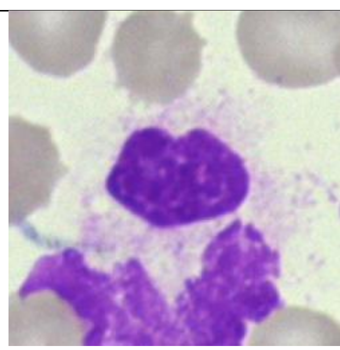
34	EBO_00033		421Kb	Normal
35	EBO_00034		321kb	Benign
36	EBO_00035		328kb	Malignant
37	EBO_00036		444KB	Normal

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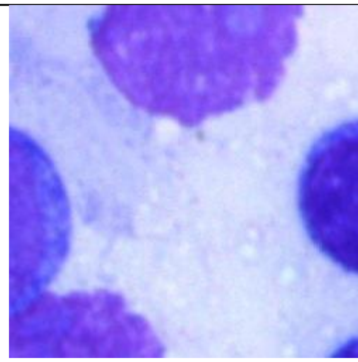
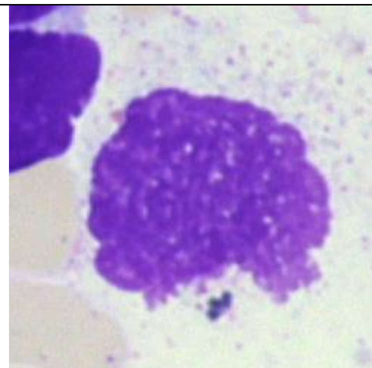
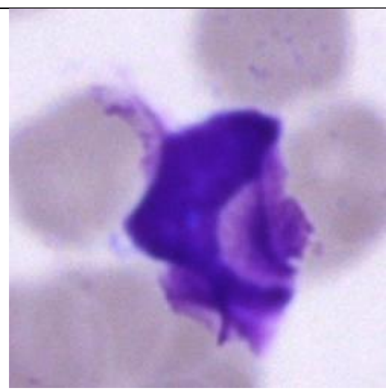
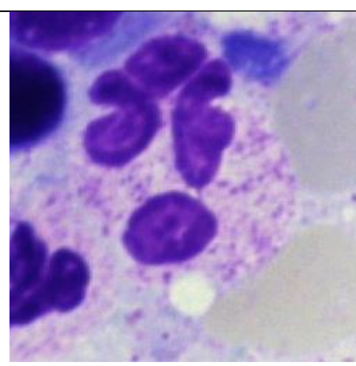
38	EBO_00037		666KB	Benign
39	EBO_00039		501KB	Malignant
40	EBO_00040		522KB	Normal
41	EBO_00041		432Kb	Malignant

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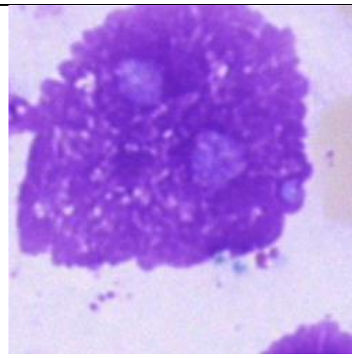
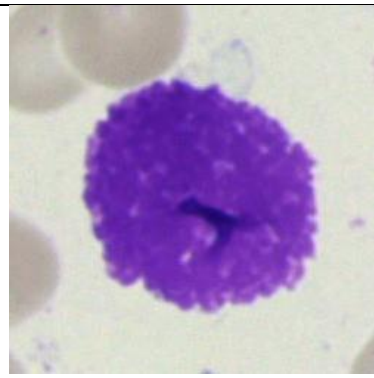
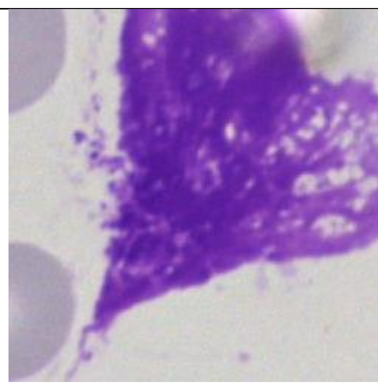
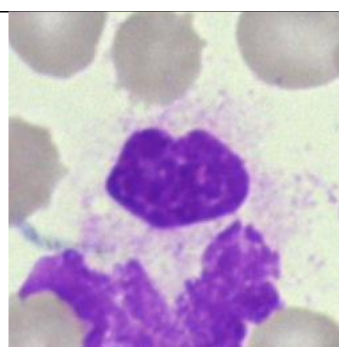
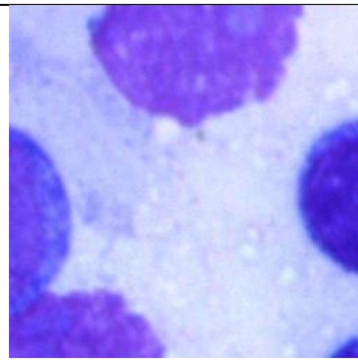
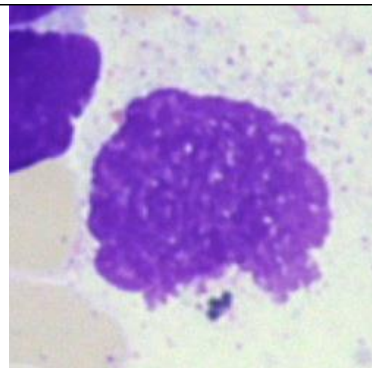
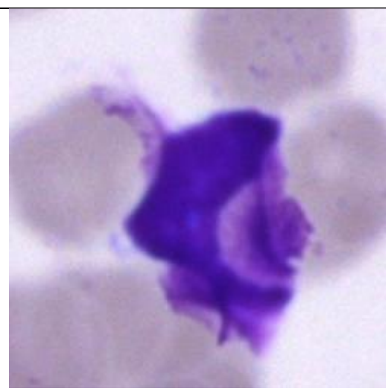
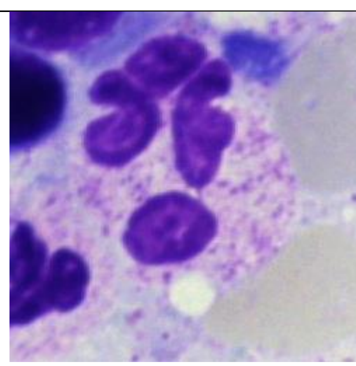
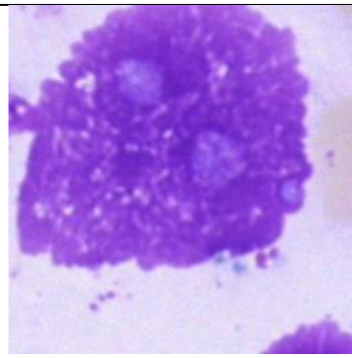
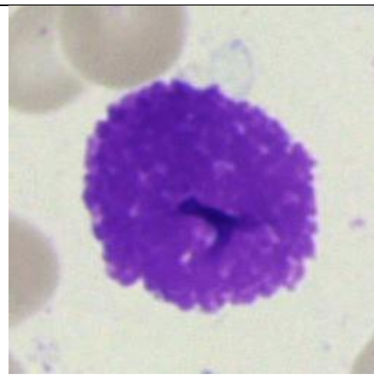
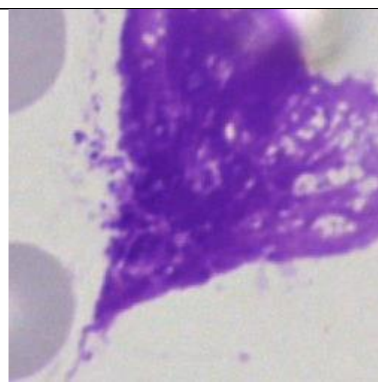
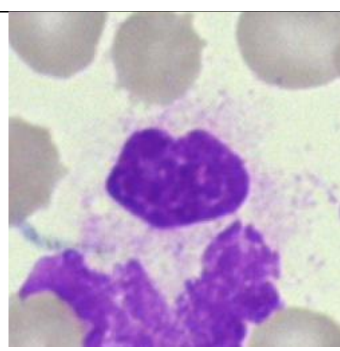
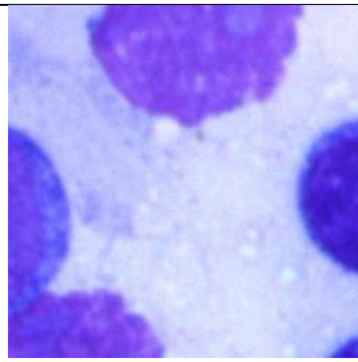
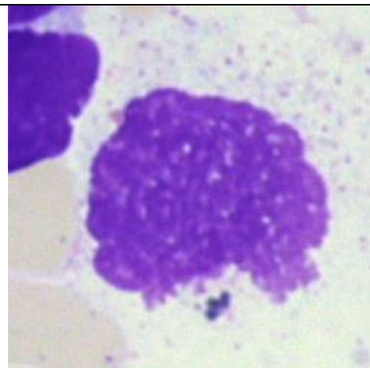
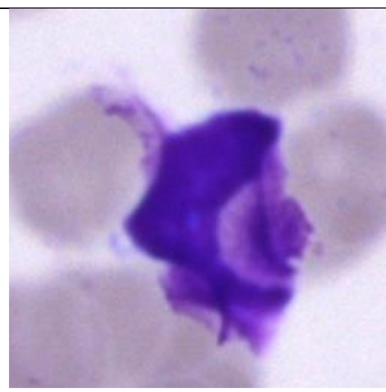
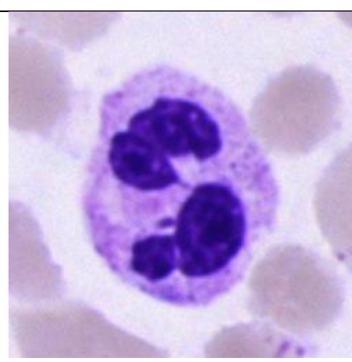
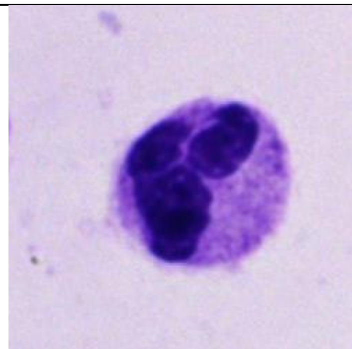
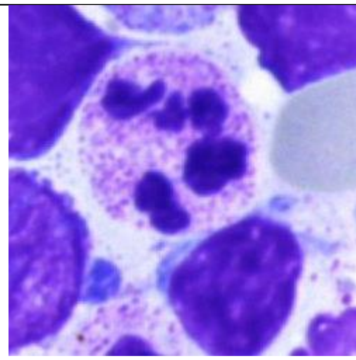
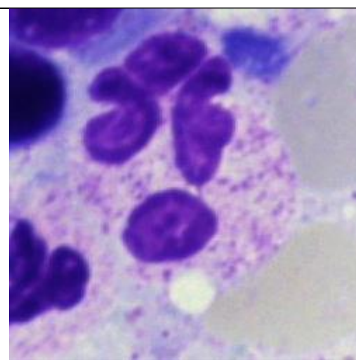
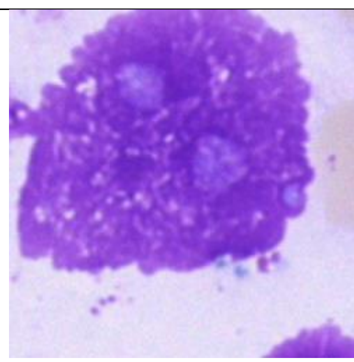
42	EBO_00045		421Kb	Normal
43	EBO_00046		321kb	Benign
44	EBO_00047		328kb	Malignant
45	EBO_00048		444KB	Normal

46	EBO_00049		666KB	Benign
47	EBO_00050		501KB	Malignant
48	EBO_00049		522KB	Normal
49	EBO_00050		432Kb	Malignant

50	EBO_00051		421Kb	Normal
51	EBO_00052		321kb	Benign
52	EBO_00053		328kb	Malignant
54	EBO_00054		444KB	Normal

55	EBO_00055		666KB	Benign
56	EBO_00056		501KB	Malignant
57	EBO_00058		522KB	Normal
58	EBO_00061		600KB	Benign

59	EBO_00062		543KB	Malignant
60	EBO_00063		512KB	Normal

61	EBO_00066		432Kb	Malignant
62	EBO_00067		421Kb	Normal

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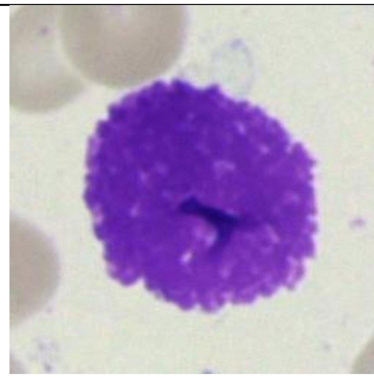
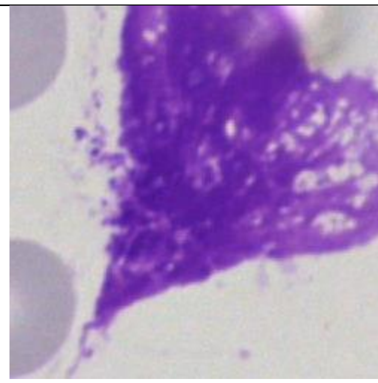
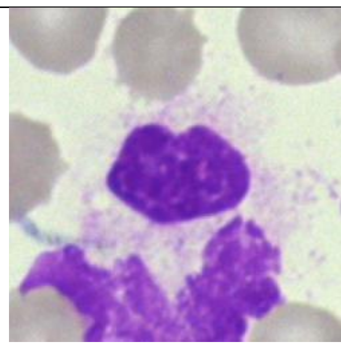
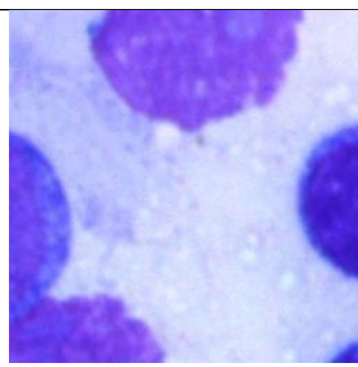
63	EBO_00068		321kb	Benign
64	EBO_00064		328kb	Malignant
65	EBO_00065		444KB	Normal
66	EBO_00066		666KB	Benign

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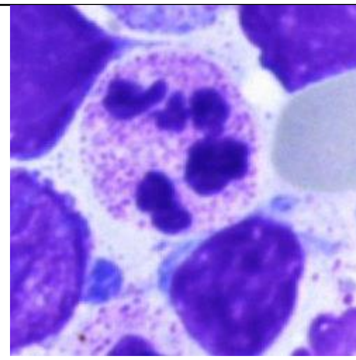
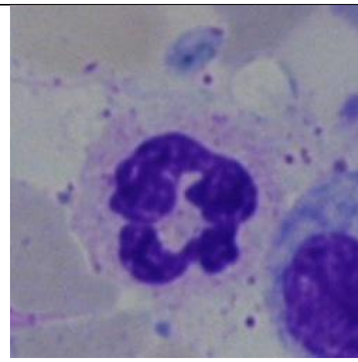
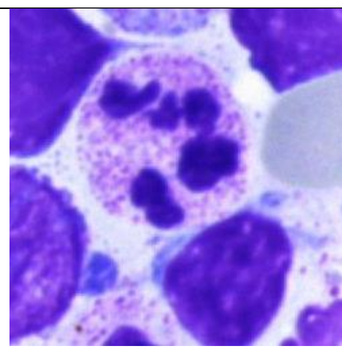
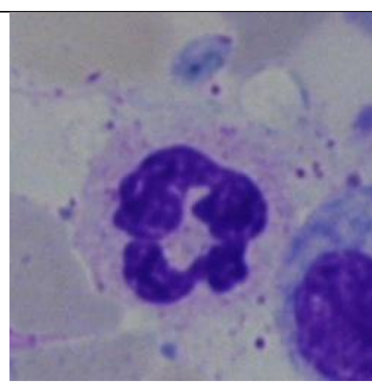
67	EBO_00069		656KB	Normal
68	EBO_00070		555KB	Malignant
69	EBO_00070		500KB	Normal
70	EBO_00067		465KB	Benign

CONCLUSION & FUTURE ENHANCEMENTS

5.1 CONCLUSION
The project is detect the bone effect areas using image processing technologies with the better algorithm is in neural network families with the best technologies of segmentation, feature extraction, pre-processing and clustering. The theme of the project is detection of the affected area using with identification with the percentage based. For the next generation will be used remain technologies with the accuracy based with the suggestions.
In conclusion, a convolutional neural network (CNN) is an artificial intelligence algorithm that presents remarkable capabilities for forensic image analysis.

5.2 FUTURE ENHANCEMENTS

Bone cancer is a serious disease that requires early detection and accurate diagnosis for effective treatment. In recent years, deep learning algorithms, specifically Convolutional Neural Networks (CNNs), have shown promising results in detecting and classifying bone cancer from medical images. The use of CNN algorithms for bone cancer detection is a valuable tool in medical diagnosis. It allows for accurate detection and classification of bone cancer, which can lead to early intervention and improved patient outcomes. However, there is still a need for improvement in the performance of these algorithms, specifically in terms of reducing false positives and false negatives.

In the future, enhancements can be made to CNNs for bone cancer detection through the development of larger datasets that can provide more diverse and accurate information for training. Additionally, the integration of other types of medical data, such as genetic information, can further improve the accuracy of bone cancer detection using deep learning algorithms.

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