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DEEP-BNET: A NOVEL ARCHITECTURE OF DEEP-BONE NETWORK LAYER BASED BONE CANCER DETECTION AND CLASSIFICATION

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Abstract

There are many types of cancer, but bone cancer is one of the deadliest and the rarest. Although its incidence is low, it has increased over the past years. An early diagnosis of bone cancer is important as it prevents the spread of cancerous cells and reduces mortality. Classical manual detection techniques are very tedious and require expert knowledge. To address these issues, the Deep-BNET model, a deep learning method using VGG19 for feature extraction, is presented. The system uses a process of transfer learning by using a pre-trained convolutional neural network (CNN), which processes pre-processed input images and extracts features of importance. The aforementioned features are applied to and utilized by an ensemble classifier for either cancer or healthy bone tissue differentiation. The virtue of CNN is that its capability of image learning can become enhanced with the increase of the depth of the network. Deep-BNET in particular employs the VGG19 model for feature extraction on X-ray images. Then a mutual information-based measure accesses the correlation between the features and selects the most informative ones, a new methodology never before used in the area of bone cancer detection. These features are then categorized into malignant and benign types by the ensemble model. Performance evaluations confirm that Deep-BNET is very efficient, 98.8% accuracy and better than other detection techniques.

Index Terms—Bone Cancer, X-Ray Images, VGG19, Pre-trained Model, Deep-CNN, Feature Selection.

I. INTRODUCTION

Bone cancer, a rare type of cancer but a deadly one, encompasses primarily the osteosarcoma and the metastatic bone cancer. Osteosarcoma primarily occurs in children and young adults and is a cancer that starts in the bone-forming tissues. Metastatic bone cancer, in contrast, is caused by the spread of cancer cells from other primary tumors in the body to the bone. Prompt detection of a bone cancer continues to be a determining factor for successful treatment and survival of the patient. Early diagnosis permits oncologists to design the most precise treatment schedules, with the potential to decrease disease-related death and morbidity [1]. Nevertheless, the diversity in the clinical presentation of bone tumors creates significant challenges for early diagnosis and therapy. Heterogeneity in tumor location, size, and histology sometimes makes it difficult to differentiate between benign and malignant lesions and calls for advanced diagnostic instruments [2]. Additionally, the fact that bone cancers are relatively rare and that many imaging features of bone tumors overlap, necessitates sensitive and specific diagnostic modality in order to improve patient outcome [3].

Recent advances have further supported that through the combination of machine learning and radionics, diagnostic accuracy could be augmented. In particular, the use of hybrid diagnostic systems based on the combination of deep learning with classical machine learning schemes has shown some potential to increase classification accuracy of MRI images for bone cancer diagnosis. The importance of early and accurate screening for osteosarcoma epitomizes the oncological need to improve prognosis by developing more efficient diagnostic work-up [4]. In addition, the review studies demonstrate issues faced in bone cancer, for instance limited annotated data, diverse in clinical appearances that are further solved by the robust hybrid methods [5].

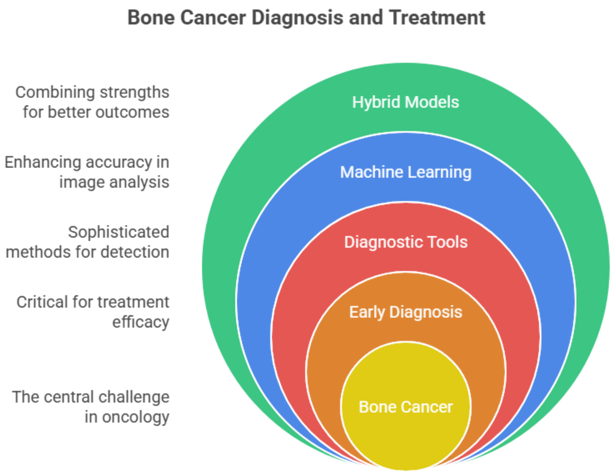

Fig.1 Bone Cancer Detection Methodologies

In terms of automatic processing, state of-the-art machine learning techniques have been applied to enhance the detection rate using different segmentation and classification techniques. Methods such as Support Vector Machines (SVM) [6], k-Nearest Neighbours (k -

NN) [7], decision trees [8] have been used for the classification of bone lesions, where handcrafted features are extracted from medical images. Nevertheless, these methods are typically confronted by the high-dimensionality and complexity of the image information, so that are not always generalization and robustness. Researchers have addressed the requirement for better developed paradigms that enable effective integration of feature extraction and classifier in a single process, particularly, facial images and radiological images as a whole.

Deep learning (DL), in particular convolutional neural networks (CNNs), has achieved a revolution in medical image analysis, including automatic bone cancer categorization [9]. The power of DL is its capability to efficiently learn complex, nonlinear mapping between image representations, without depending on manual engineered features, thus bypassing traditional bottlenecks of hand-designed descriptors. The application of CNN models to different types of medical images, such as X-rays, CT, MRI scans, has resulted in significant enhancement of accuracy and reliability of cancer detection tasks [10].

Hybrid deep learning architectures are recently developed methodologies that combine deep learning algorithms and classical or complementary feature extraction techniques to improve the detection and classification of bone cancer. The architectures exploit the representative power of CNNs to extract high-level semantic features and making a fine-tuning on the classification performance by using additional machine learning classifiers as SVM, GBM, and MLP [11]. Hybrid approaches frequently provide superior generalization, feature separation and prediction accuracy to independent models by integrating strengths from both worlds.

II. RELATED STUDY

In [12], the author proposed a new automated pipeline, OSADL-BCDC (cognized as the Owl Search Algorithm with Deep Learning-Driven Bone Cancer Detection and Classification). This architecture combines the latest techniques in deep learning, namely transfer learning using the Inception v3 out of the box convolutional neural network. This design decision eliminates the need to perform manual image segmentation, simplifying the feature extraction, and the model. Additionally, the work utilizes the Owl Search Algorithm (OSA) a heuristic algorithm for optimizing the performance of the estimated critical hyper-parameters of the Inception v3 network. This hyperparameter optimization is key in order to guarantee the robustness and versatility of the network with complex medical imaging modalities. In addition, LSTM Networks is incorporated in the model to take advantage of their ability to learn temporal pattern and improve detection sensitivity and specificity for identifying the presence of bone cancer. Experimental results with the OSADL-BCDC framework show significantly faster convergence in training and improved diagnostic performance with respect to the state of the art algorithms.

A very in-depth study of deep learning applied to early detection of bone cancer, namely osteosarcoma, a deadly and common type of bone cancer is presented in [13]. In this work, the author report on a lesser complex problem of reservoir inflow forecasting. They emphasize the prevention and early diagnosis to save patients by controlling the process of

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metastatic dissemination of malignant cells. Various medical shots have been used for bone cancer studies, including histology and radiology, as well as even more advanced scanning technologies like PET and MRI, however, we highlight the important diagnostic features provided in a H&E stained histology images for early detection of osteosarcoma. Acknowledging the limitations and limited performance of traditional Convolutional Neural Network (CNN) models in the context of medical image analysis, the authors aim to address these issues by optimizing the model empirically. In this work they introduce a new specialized CNN architecture, named as Bone Cancer Detection Network (BCD-Net), specifically developed for improving the automatic detection of osteosarcoma from histo-pathological images. The BCD-Net forms the backbone of a new method, Learningbased Osteosarcoma Detection (L-OD), that implements the model for binary (cancerous versus non-cancerous) as well as multi-class classification tasks, which capture subtleties in tumor characterization. The Osteosarcoma-Tumor-Assessment (OSTA) dataset, which is a set of H&E stained histo-pathological images was used in the empirical analysis to evaluate BCD-Net. Results show that BCD-Net outperforms the competing basic methods by the achieved high classification accuracies of 96.29% on binary task and the 94.69% on multi-class one.

The work in [14] considers the very difficult task of diagnosing primary bone tumors in radiographic images, emphasizing the inherent difficulty in achieving accurate and timely diagnosis that often mandates the involvement of specialist expertise. The nature of an early diagnosis, particularly for a malignant bone tumor (which is among the most prevalent causes of cancer mortality in adolescent and young adult patients) makes the research particularly timely and demonstrates the increasingly urgent need for automated, dependable diagnostic resources to complement the clinical decision-making process. In order to do so, the paper designs and critically evaluates a deep learning method based on the Faster R-CNN framework with a Res-Net backend structure. In this method, they exploit state-of-the-art convolutional neural networks to detect, and also classify benign versus malignant, primary bone lesions on radiographs. Using the publicly available Bone Tumor X-ray Radiograph (BTXRD) dataset for training and testing, the author show that the model is highly effective in detecting the relevant tumor features, and in labeling them as pathological.

The work [15] indicates the importance of bringing together a computer science approach with biological knowledge to improve the diagnosis for bone cancer detection, which is particularly relevant in the context of imaging techniques such as X-ray and MRIs scans. The demand for concurrent and sophisticated diagnostic procedures is then of critical importance: in the current scenario rapidly advanced medical imagery techniques are used and sophisticated imaging devices are required in order to address the growing complexity and demand in the health care domain. At the heart of this mission is the use of advanced image processing techniques, where Watershed segmentation is essential for precise segmentation of the boundary of the tumor.

III. METHODOLOGY

In this section provides the introduction of a hybrid Deep-CNN-Ensemble based architecture for the Deep-BNET based bone cancer detection system. In this paper, hybrid system includes CNN and ensembles learning; CNN is good enough with feature extraction but ensures to have good classifier performance. The development of the hybrid model at this intersection to confront challenges in medical image analysis, including tumour appearance variability and lack of annotated data, by utilizing the representation capabilities of convolutional neural networks with the generalization power of ensemble methods.

At the core of Deep-BNET system is the VGG19 model, known as a classic deep convolutional neural network (D-CNN) with tiered layers. And indeed, VGG19 is not even that deep, only 19 layers, but it allows you to learn features with various levels of abstraction, which is important for effective pathological changes in the images of the bone tissue. This pre-trained network can be used in transfer learning by using the weights from the previously learned feature representation from learning on a massive image database as VGG19 for visual representations. This transfer learning methodology minimizes the amount of bone cancer-specific training data required to achieve high feature discriminability, thereby improving the accuracy of the subsequent classification stages. After feature extraction, the above detailed representations are all fed into an ensemble learning framework for better training efficiency and to achieve more robust diagnosis accuracy.

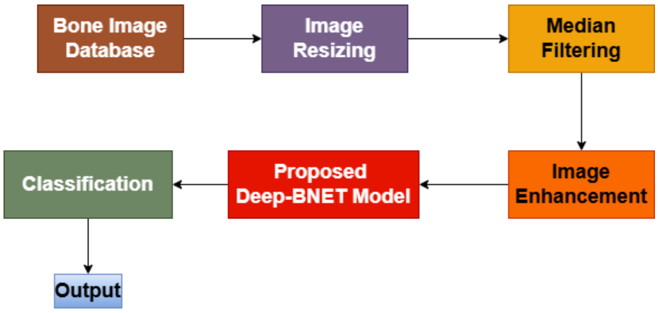

Fig.2 Proposed Methodology Flow

Ensembles learning involves the combination of predictions across a range of layers that eliminates individual layer performance and decreases over-fitting of deep learning in medical images. By methods of bagging, boosting or stacking the ensemble model composites a varied combination of decision boundaries resulting in a more stable and accurate detection of bone cancerous images. This consensus process in making decisions is key in this system to achieve quick and correct classifications of much importance in proper clinical interventions. Designing the Deep-BNET system will not only increase diagnostic accuracy, but also will succeed in quickly detecting the existence of cancer images because the most important need in clinical diagnosis is immediate.

The architecture of this system can guarantee efficient processing due to lean feature extraction and ensemble training initiatives thereby cutting on computational overhead as well as allowing the system to be depicted in real-time. A visual summary of the sequential processes and components of Deep-BNET pipeline is depicted as an overview of this sophisticated system flow is illustrated in Figure 2.

The pre-processing methods (median filtering) are often used to suppress extreme noise value, because most of image data tends to have noise. Such a step is fundamental as the reduction of noise greatly enriches the results of the following image analysis. Contrarily other filters, the median filter helps to sharpen the input images and to keep significant edges and details, avoiding smooth effects. The Median filtering operation as follows,

$$g(x, y) = median\{N(g)\} \qquad (1)$$

The variable $N(g)$ are the nearing pixels of the Image.

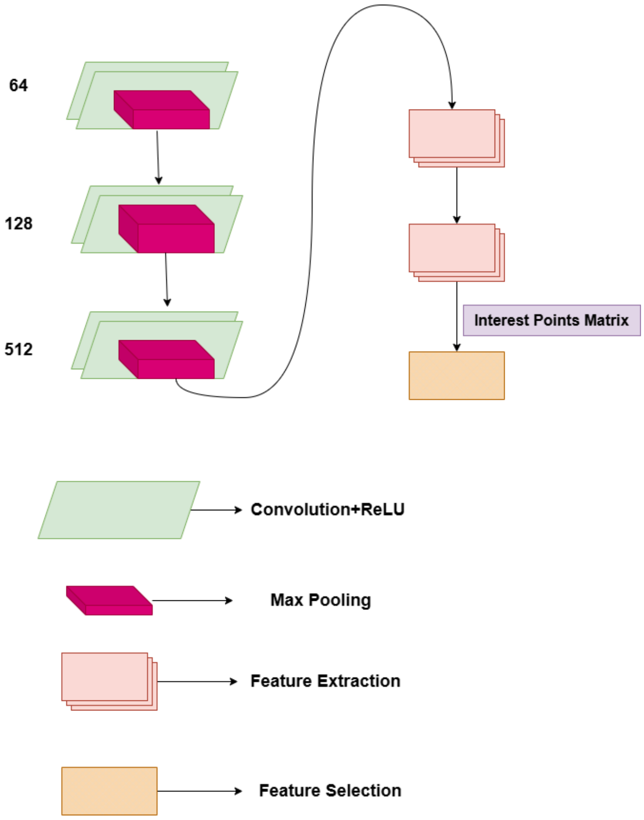

Fig.3 Proposed Deep-BNET Model Architecture

The model VGG19 automatically makes its feature extraction and this feature extraction is forwarded to the classifier to be processed. The feature extraction employed in Deep-BNET system derives only on the convolutional layers, the pooling layers and the initial fully connected layers which are always processed in the same order of convolutional and max-pooling functions. Convolutional layer is the initial step in the process of feature recovery on the image data where the operation of convolution is performed on the original image that is received. The architecture of the proposed model shown in Figure.3. The convolutional layer operation as follows in equation (2),

$$(g \oplus K)[r, s] = \sum_{m} \sum_{n} g[r - m, s - n] \, K[m, n] \qquad (2)$$

The variable $\oplus$ is the convolutional operator, K represents the utilized size of the kernels and the variable $[r, s]$ represents the feature map matrix of the image.

The convolutional layer is a key component of the Deep-BNET system since it produces the feature map that is a critical mid-level representation of the input data. This layer performs

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various filters on the input, extracting different spatial and contextual features, such as edges, textures, and some certain patterns, which characterize the underlying structure of the data. These properties are then contained in the feature map, which is represented as a multi-dimensional matrix, in which the underlying information for further processing remains. Quality and resolution of this feature map greatly affects the performance of the network as it serves as the foundation for higher level abstractions and classifications. After the convolutional layer, the generated feature map will be taken as input for the max-pooling layer, a dimensionality-reduction method for efficiency and robustness of the system. Max-pooling involves sliding a fixed-size window across the feature map and taken the maximum value within each window, which allows for a reduction in the spatial dimensions of the feature map without discarding the most important activations. This down sampling reduces both the computation complexity and the model size, and can greatly alleviate over-fitting by introducing certain degree of translational invariance.

Algorithm: Proposed Deep-BNET model Classification

1. Input: Bone X-Ray Image from bone database
2. Output: Predicted and Classified output Image Y_I
3. Read the Input Image
4. Perform Input Image Resizing
5. Removal of the Noise from the Image using Median Filtering
6. Feature Extraction using $f <-feature_{extraction}(g)$
7. Selection of the best features

$$f_s = selectKbest(\quad);$$

8. Classification of the Test image using Trained Selected Features
9. Return the Predicted Output
10. End of the Algorithm

In turn, the model is made to be more robust to perturbations in the input data which is critical in practice where a variability in input is typical. Furthermore, this step of max-pooling simplifies the model structure causing accelerated convergence of the training process and better generalization properties. This action of successively decreasing the spatial dimension of the feature maps has the strength to filter out redundant data keeping only important elements that are required to make accurate predictions. This dimensional reduction also allows going deeper with the architectures by letting the network have additional layers without causing exponentially more computational usage. Hence, max-pooling plays a two-dimensional role of improving the computational feasibility as well as the practical functionality of Deep-BNET system. In order to summarize these processes, a complete overview of the suggested Deep-BNET system has been formulated in the Algorithm provided. The sequential steps of this algorithm are described as processing the inputs by using convolution filters, then by using max-pooling and other downstream

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operations and in this way, it presents an intense and systematic outline of the implementation and further investigation.

This output layer will simplify the neural network architecture and help prevent over-fitting, which can happen when a model learns noise or other features in the training data that do not generalize to other situations. This layer yields better generalization to unseen data and better overall performance by shrinking the complexity for the proposed model. Normally, fully connected layers are located at the end of the network architecture, acting as an intermediate connection between low-level learned features (from previous layers) and the final prediction output. In reality, the signal-output of the last pooling or convolutional layer (consisting of multi-dimensional feature maps) needs to be vectored and thus turned into 1-dimensional input matching fully connected layers. This transformation enables the model to pool spatially distributed information represented with convolutional filters to use them as input features for classification or regression problems. Here, then the information is propagated across both features and neurons to generate expressive representations required to make predictions. After the first fully connected layer, crucial features are chosen. This is realised through the use of mutual information statistics, a statistic for describing the dependency or information shared between random variables, the features and the target output in this case. Mutual information is also a robust measure of relevance as it identifies features that contribute the maximum information gain given the prediction task.

It uses entropy-based measurements to produce a ranking of features to use and select among. It is important to apply feature selection at this step due to a set of reasons. First of all, it can be used to remove duplicated or irrelevant predictors which do not assess any more information that may cause the complexity of a model to rise and even cause over-fitting to occur. Not only the model is able to obtain increased predictive accuracy by pruning such features, but also efficiency is added as the time required to train the model decreases owing to the dimensionality reduction of the input data. This proposed optimization makes it easier to converge and train the proposed model to allow their models lean and interpretable in an effort to generalize well on new data.

IV. RESULTS AND DISCUSSION

The Deep-BNET model is trained on an extracted bone cancer X-ray image dataset collected from Indian Institute of Engineering Science and Technology (IIEST) repository. This dataset is an essential building block for training and testing the model and consists of 120 images. These images fall directly in the middle of two vital categories: 60 images of normal bone structures and the other 60 images are of bone cancerous conditions. Such a balanced distribution makes the system to be well-trained by a representative and unbiased sample of both classes and is very essential for establishment of non-biased diagnostic future.

The resized images to 225×225 pixel resolution are then standardized in both two databases in order to ensure the stability of analysis and the robustness of Deep-BNET system. This rescaling is beneficial to match input scales, reduce numerical and computational burden and allows the neural network to effectively process images without losing significant diagnostic information. Consistent image dimensions further help in reproducibility of results, and

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facilitating easy incorporation of the images in deep learning framework. The proposed model's input is illustrated in Figure 4. In combination with the balanced dataset and consistent pre-processing procedures, the Deep-BNET system are well-founded in its ability towards accurate classification of bone cancer from X-ray images.

Fig.4 Input Image

Fig.5 Input Image to Median Filtered Image

A standardized image undergoes the process of resizing which is explicitly followed by application of a median filter as shown in Figure 5. The median filtering method is also widely applicable to reduce impulse noise and at the same time maintain relevant edges and structural information in the picture. The median filter, unlike a linear smoothing filter, retains major features by averaging the intensity (neighborhood) of the pixel values with the median value rather than the mean. This filtration maximizes clarity and sharpness of the visual information, and therefore makes it more adaptable to downstream activity of feature extraction. The result of such filtering is an impressively clearer and more detailed image as can be seen in Figure 5.

Fig.6 Enhanced Image using CLAHE

The segmentation technique achieves higher contrast enhancement while leading to visually pleasant results and preserves image unaffectedness. The basic idea of the CLAHE is to restrict the contrast amplification (i.e., the upper limit of the amplification factor) in order to

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prevent over-enhancement by clipping the histogram of each tile. This clipping level effectively bounds the height of the histogram bins by distributing the clipped pixels evenly over all histogram bins. In this way, CLAHE avoids the excessive contrast amplification of conventional adaptive histogram equalization methods. This knife-edged amplification does not only makes the visibility of characteristics better under different light conditions, noise over detection as shown in Figure.6.

The Figure.7 presents an interest point on an image, it is a particular characteristic location in the visual scene with some unique or conspicuous features that have special appeal in conducting the task of bones cancer location tracking. These are the aspects that contrast with the direct environs as a result of the differentiation in the level of intensity, color, texture, or even geometric form. The qualities desired of a good interest point are uniqueness, being repeatable, and robust. All of these properties ensure that the interest point should not only extract meaningful data, but also provide consistency in different imaging situations. The detection of interest points is normally done using suggested algorithms that examine the local areas of the picture to identify locations that have drastic variation in intensities.

Fig.7 Proposed Deep-BNET based Interest Points

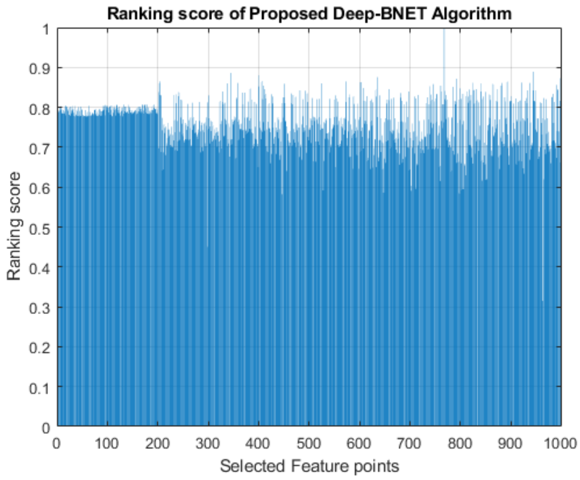

Fig.8 Proposed Deep-BNET Protocol based Ranking Score Prediction

The Figure. 8, where point-based features usually indicates the local descriptors detected in the salient regions of an image. These features extract fine-grained local structure, such as edge and corner, which is very useful for tasks that need precise discrimination between objects despite their orientation. These point features in combination with multiple image representation permit a fine-grained analysis of the image data since images are characterized

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as sets of such local descriptors and compared in between images in terms of the similarity. Ranking scores represent the output of an image ranking trained with proposed classification model scoring and ordering images by the relevance of images to a class.

The Figure.9 shows the confusion matrix obtained from our proposed Deep-BNET model. From this matrix, our model achieves the overall accuracy of 98.8% with the loss value of 0.418%. These values show our proposed model performs the perfect classification of test image with respect to the training images based trained model.

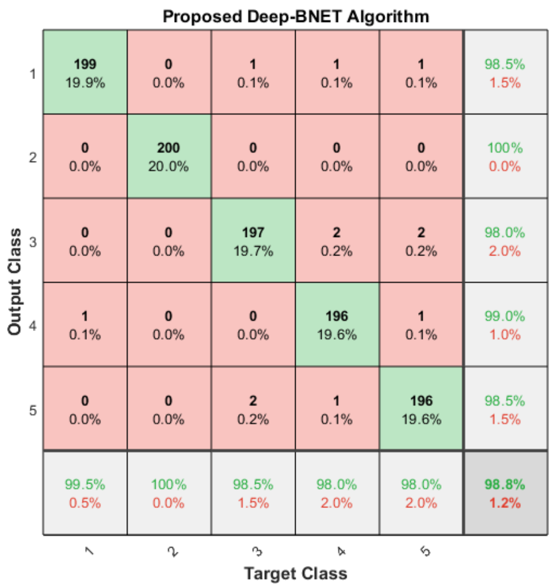

Fig.9 Confusion Matrix of Proposed Model

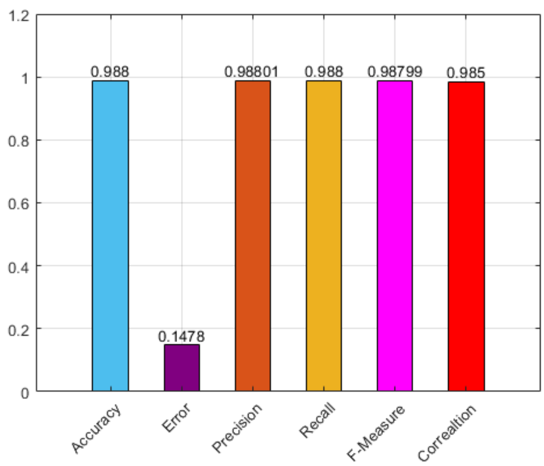

Fig.10 Overall Performance Metric Comparison of Proposed Deep-BNET Model

Figure. 10 shows a summary of the performance results of our proposed model as an achievement and demonstrates the effectiveness of our model in multiple evaluation measures. The model achieves an accuracy of 98.4%, which means a high proportion of the correct prediction among those examined. This level of accuracy demonstrates the robustness of the model in generalizing from the training data to the unseen samples, and the confidence of the model toward the classification results. Apart from accuracy, recall parameter was of an outstanding 98.9%, which showed the model's performance in detecting bone cancer correctly. High recalls are particularly important for tasks in which false negative cases can have a big impact. This performance shows that the model avoids drawbacks like false negatives, being able to identify most relevant cases in evaluation. In addition to recall, the high precision measure of 98.8% confirms the model's potential to control the false positive estimates. This trade-off between precision and recall indicates that the model has a trade-off between false positives and true positives, and it goes for trading off the proportion of both cases mentioned earlier and predicts cancer positive. And last, the F1-Score of 98.7% expounds these qualities into a single harmonic mean, which balances the model's ability to classify. The similar value of the F1-Score to precision and recall illustrates reliability of the testing results to avoid having too many false positives and at the same time false negatives. Together these metrics in Figure 10, demonstrate the effective predictive capability of the resulting model with consistent and balanced classification numbers.

Conclusion

Bone cancer is an uncommon condition and it may spread to the other parts of the body. Manual inspection of bone cancer is difficult and it demands enough expert knowledge for a high reliable and accurate process. An approach to overcome this was presented for X-ray images with a Deep-BNET system built on a CNN based ensemble model. The proposed Deep-BNET system uses mutual information statistics for feature selection. VGG19 was discovered to be the best performing model when compared with the other models that were used for ensemble and feature extraction when comparing the various models. The percentage of accuracy achieved using the proposed machine is 98.8%, which is superior than others of its type. The following aspects can verify if the model be feasible in the future. The performance of the proposed Deep-BNET could be enhanced by training with large datasets instead of small datasets.

References

[1] Ramamoorthy, Ramesh and Dr.R.S.Shanmugasundaram. 2025. "An Investigative Framework for Bone Cancer Detection Using Deep Learning". Journal of Information Systems Engineering & Management. https://doi.org/10.52783/jisem.v10i4.10382

[2] Borji, Arezoo, Kronreif, G., Angermayr, Bernhard, and Hatamikia, S. 2025. "Advanced hybrid deep learning model for enhanced evaluation of osteosarcoma histopathology images". Frontiers in Medicine. https://doi.org/10.3389/fmed.2025.1555907

[3] Kaur, Er. Charnpreet and Garg, Urvashi. 2022. "Bone Cancer Detection techniques using Machine Learning". None. https://doi.org/10.1109/ICCMSO58359.2022.00068

[4] Walid, Md. Abul Ala and Shill, P. C. 2023. "A Transfer-Learning Based Unbiased Voting Bone Cancer Detection Framework from Histological Osteosarcoma Images". International Conference on Computing Communication and Networking Technologies. https://doi.org/10.1109/ICCCNT56998.2023.10307768

[5] Lalitha, Ms. M. 2025. "Automated Bone Tumor Detection Using Deep Learning: A CNN-Based Approach For Enhanced Diagnostic Accuracy". None. https://doi.org/10.55041/ijsrem47419

[6] S, Murugan, Patil, Shravani S, V, Shree Deeksha, Reddy, Rohith K, and N, Shravanth Kumar K. 2024. "A Recent Survey on Bone Cancer Detection Using Deep Learning Techniques". International Conference on Advanced Infocomm Technology. https://doi.org/10.1109/ICAIT61638.2024.10690575

[7] Jiang, Xiaoyan, Hu, Zuojin, Wang, Shuihua, and Zhang, Yudong. 2023. "Deep Learning for Medical Image-Based Cancer Diagnosis". Multidisciplinary Digital Publishing Institute. https://doi.org/10.3390/cancers15143608

[8] Sistaninejhad, Bagher, Rasi, Habib, and nayeri, Parisa. 2023. "A Review Paper about Deep Learning for Medical Image Analysis". Hindawi Publishing Corporation. https://doi.org/10.1155/2023/7091301

[9] Aziz, Md. Tarek, Mahmud, Sakib, Elahe, MdFazla, Jahan, Hosney, Rahman, Md Habibur, Nandi, Dip, Smirani, Lassaad K., Ahmed, Kawsar, Bui, Francis M., and Moni, Mohammad Ali. 2023. "A Novel Hybrid Approach for Classifying Osteosarcoma Using Deep Feature Extraction and Multilayer Perceptron". Multidisciplinary Digital Publishing Institute. https://doi.org/10.3390/diagnostics13122106

[10] Kanyal, H. S., Joshi, Prakash, Seth, Jitendra Kumar, Arnika, and Sharma, Tarun Kumar. 2024. "A Hybrid Deep Learning Framework for MRI-Based Brain Tumor Classification Processing". International journal of experimental research and review. https://doi.org/10.52756/ijerr.2024.v46.013

[11] Sampath, Kanimozhi, Rajagopal, Sivakumar, and Chintanpalli, Ananthakrishna. 2024. "A comparative analysis of CNN-based deep learning architectures for early diagnosis of bone cancer using CT images". Scientific Reports. https://doi.org/10.1038/s41598-024-52719-8

[12] K, Deepak Kumar, S, S., K, Mahalakshmi, G, Madhulika, and R, P. 2025. "Integrating Unet Segmentation and Vision Transformers for Improved Bone Cancer Diagnosis in Histopathological Images". International Conference on Computing and Convergence Technology. https://doi.org/10.1109/ICCCT63501.2025.11020476

[13] Song, Liwen, et al.. 2024. "A deep learning model to enhance the classification of primary bone tumors based on incomplete multimodal images in X-ray, CT, and MRI". Cancer Imaging. https://doi.org/10.1186/s40644-024-00784-7

[14] Dalai, PhD SasankaSekhar, Sahu, PhD Bharat JyotiRanjan, Rautaray, PhD Jyotirmayee, Khan, PhD M. Ijaz, Jabr, PhD Bander A., and Ali, PhD Yasser A.. 2024. "Automated Bone Cancer Detection Using Deep Learning on X-Ray Images". Surgical Innovation. https://doi.org/10.1177/15533506241299886

[15] Rao, BolledduDevananda and Madhavi, K. 2024. "BCDNet: A Deep Learning Model with Improved Convolutional Neural Network for Efficient Detection of Bone Cancer Using Histology Images". International Journal of Computational and Experimental Science and Engineering. https://doi.org/10.22399/ijcesen.430