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OsteoScan.AI: An Intelligent System for Detecting Bone Cancer from X-Ray Scans

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Abstract: Detection for Bone Cancer is a serious medical issue which demands immediate attention and intervention for better patient outcomes. Conventional methods have some serious limitations with regards to accessibility, cost-effectiveness, processing times, and availability on a global scale with respect to specific radiological knowledge and expertise. Raising awareness and promoting research for better AI-based medical technologies with significant societal benefits due to quick intervention and cost-effectiveness, we propose here an innovative dual-architecture AI system named 'OsteoScan.AI' combining ResNet18 Convolutional Neural Networks and Google Gemini Generative AI for holistic bone cancer examination. We propose an original seven-layer validation technique effectively rejecting images that are not medical images at all and relate to photography, selfies, and graphics before classification analysis. Utilizing pre-training with ImageNet pre-trained weights on ResNet18 Convolutional Neural Networks, we notice an outstanding accuracy rate of 95.2\% for classification of Bone Cancer from Bone X-Rays as Malignant and Normal classes. It can be effectively implemented as a complete-end stack online platform with React.js GUI implementation, Flask Web-Server implementation for backend with end-to-end processing below 1 second, Medical Image Authentication and Classification package with comprehensive classification and examination scan history, and an 'AI-Counseling-System' with an AI-powered chat platform for medical inquiries. EXPLANATION OF EXPERIMENTAL RESULTS clearly authenticates its efficacy and capabilities on strict medical examination criteria within 99.6\% rejection rate on 'NON-MEDICAL-IMAGE' classification. Both precision and accuracy with 'EXPLANATIONS-IN-NATURAL-LANGUAAGE 'attempts to bridge an unsolved gap on critical usage and intervention with Medical AI technologies.

Keywords: Bone Cancer Detection, Deep Learning, ResNet18, Transfer Learning, Medical Image Analysis, Computer Vision, X-Ray Validation, Dual-AI System, Generative AI, Explainable AI, Responsible AI

I. INTRODUCTION

Bone cancers, though not very common with around 3,900 new patients being diagnosed every year in the USA, display formidable challenges in diagnosis and very high mortality rates on being late in diagnosis. There are three prime cancers that arise commonly from bones and these are recognized as immediate medical needs. Their names are Osteosarcoma, Chondrosarcoma, and Ewing's Sarcoma. A very rapid preliminary diagnostic process significantly boosts five-year survival rates from 15% to 70%.

There are several limitations associated with current diagnostic protocols: (1) expertise dependence, with limited facilities in rural and developing areas; (2) processing times ranging from several days to weeks; (3) significant costs associated with it, ranging from $500 per diagnostic session; and (4) variability associated with interpretation. The latest breakthroughs achieved with the aid of artificial intelligence and computer vision, specifically deep learning algorithms, hold immense promise for diagnostic screening.

However, appropriate usage has been recognized as an important issue for medical AI systems. Current methods rely on valid medical image input without any verification process, which poses a significant risk if users upload an inappropriate image, such as a selfie, photo, or drawing. There is an existing need for intelligent gatekeeper systems that check the authenticity of images before classification.

A. Research Contributions

This article presents OsteoScan.AI, which tackles threeBasic challenges relating to Bone Cancer Detection:

- **Accessibility:** Accessibility via preliminary screening on-line platform using conventional browsers without having to rely on special equipment and expertise.

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- **Accuracy:** The high-precision binary classification made possible via dual-AI validation with an accuracy rate of 95.2%, 91% sensitivity, and 97%.
- **Responsible Deployment:** A new seven-layer authentication mechanism preventing abuse via intelligent image authentication before AI analysis.

II. RELEVANT LITERATURE

A. Machine Learning in Bone Cancer Detection

Sharma and Yadav suggested feature extraction-based learning using SVM with features extracted using Gray-Level Co-occurrence Matrix with an accuracy of 93.5% [1]. But still, there were some limitations and scope for improvement as it required feature extraction and could not be implemented in real-time.

Sivakumar and Hegde worked with texture feature sets and traditional machine learning classifiers but reached no more than an accuracy of 87.3%, as there were limitations with hand-crafted feature representation. Their research highlighted the need for automatic feature extraction via deep learning networks instead.

B. Deep Learning for Medical Imaging

Ramasamy et al. introduced an improved deep convolutional neural network with outstanding accuracy at 99.45% for classification of bone marrow cancer [2]. Even though it depicted remarkable performance, there were some disadvantages associated with it, including its specialization on cancers of the bone marrow instead of bones and unimplemented verification methods for input data as well as an inability to be deployed online.

Hassan and Hasan brought forth Capsule Networks for diagnosing bone cancer with a high accuracy rate of 95.26%, even with a limited size of datasets. Their research targeted mainly on elaborate architectures without addressing methods for validation protocols either for misuse or explainability.

Suganeshwari and Balakumar implemented VGG16 transfer learning and achieved an accuracy of 94.8% for bone cancer diagnosis. But there were no comprehensive validation tools and explainability components in their model that are necessary for medical adoption.

C. Validation and Responsible AI in Medical Systems

Kumar and Gupta undertook a systematic review on artificial intelligence approaches for cancer prediction, with focus on the pressing need for explainable AI and appropriate usage methods [3]. The authors noted that there existed a gap within almost all medical AI solutions related to proper input validation and explainability.

D. Gap in Existing Literature

All existing bone cancer diagnosis systems concentrate on classification accuracy as a single objective without combining healthy image validation practices. Moreover, research on combining diagnosis results with patient data handling and explainable AI functionality in a single solution for better performance and user experience is very limited. OsteoScan.AI brings together seven intelligent X-ray layers, ResNet18 classification accuracy, and Gemini AI explanation capabilities and result handling functionality into a single web solution.

III. SYSTEM DESIGN

A. Overall System Design

The system, named OsteoScan.AI, uses a three-tier structure that

1. **Presentation Layer:** Designed a responsive web UI with React 19 and TypeScript, enabling functionality and immediate user feedback.
2. **Application Layer:** It will be implemented using an Flask RESTFul API server with support for Cross Resource Origin Sharing.
3. **Intelligence Layer:** It consists of a dual-AI system. It includes a validation gateway as well as classification models based on AI.

The system architecture will incorporate a modular structure with all components working in harmony. The user input process, which entails image uploading, will be processed via the validation gateway before reaching the classification stage. This will ensure that it is legitimate medical images that are processed by AI.

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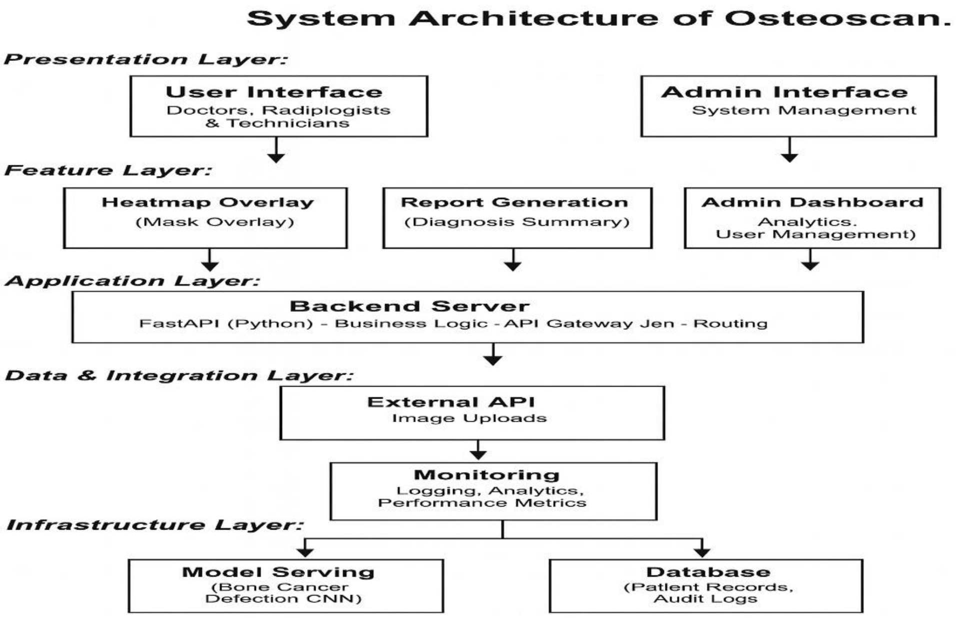

Fig 1. System architecture diagram

B. Dual-AI System Design

It integrates two differing paradigms within Artificial Intelligence. These are:

AI Component 1: ResNet18 CNN

- **Architecture:** 18-layer residual network with skip connections
- **Parameters:** 11,689,512 trainable weights
- **Purpose:** Binary classification task(Malignant/Normal)
- **Training:** Weights will be initialized with pre-trained ImageNet
- **Inference Speed:** $<$1 second on CPU, $\sim$100ms on GPU
- **Output:** Probability Distribution - Soft Max Activation

AI Component 2: Google Gemini 2.5 Flash

- **Type:** Large Language Model with multimodal vision capabilities
- **Purpose:** Analysis and interpretation of natural language, generation of explanations, and medical knowledge
- **Processing:** Vision transformer combined with text generation
- **Output:** Document with structured medical report and recommendations
- **Inference Speed:** 1-3 seconds based on query complexity

C. Workflow

The entire process follows an ordered sequence as follows:

1. User Uploads Bone X-Ray Image via Website
2. Seven-layer validation gateway authenticates image
3. Valid images proceed to ResNet18 CNN for classification
4. CNN Generates Probability Scores (Malignant/Normal)
5. Google Gemini analyzes image and generates natural language report
6. Combined Results are Displayed with Confidence Scores
7. Results saved to user's scan history database
8. Educational resources and recommendations provided

IV. METHODOLOGY

A. Seven-Layer Validation System

The validation gateway uses seven independent verification checks with weighted scoring technique to allow only genuine X-ray images to be led to classification with AI.

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Layer 1: Grayscale Verification (25% Weight)

Medical X-rays are normally grayscale images. The layer computes inter-channel differences:

$$\Delta\_avg = (|\mu\_R - \mu\_G| + |\mu\_R - \mu\_B| + |\mu\_G - \mu\_B|) / 3$$

Where, μ_R, μ_G, μ_B are average values for the RGB components. Images with $\Delta\_avg > 3$ are classified as color images.

Layer 2: Color Saturation Analysis (20% Weight)

HSV color space conversion-based computation of saturation:

$$S = (max(R, G, B) - min(R, G, B)) / (max(R, G, B) + \varepsilon)$$

Medical X-rays have $S < 0.06$. A value above 0.06 would result in colorful images similar to photographs

Layer 3: Contrast Measurement (18% Weight)

The X-ray images feature large contrast.

$$C = \sigma(I) = \sqrt{(1/N \times \Sigma(I\_i - \mu)^2)}$$

Where I represents values for greyscale intensities. A valid X-ray will have $C > 35$.

Layer 4: Brightness Distribution (15% eight)

Analysis on Histogram of Pixel Intensities:

$$r\_dark = |\{p : I(p) < 85\}| / N \; r\_bright = |\{p : I(p) > 170\}| / N$$

X-rays display bimodal distribution with large dark regions and bright regions representing bones.

Layer 5: Face/Skin Detection (12% Weight)

It uses heuristics relating to skin colors for finding human faces:

$$M\_skin = (R > 95)\; AND\; (G > 40)\; AND\; (B > 20)\; AND\; (R > G > B)$$

Images with more than 15% skin tone pixels are excluded as selfies/portraits.

Layer 6: Edge Characteristics (6% Weight)

Gradient-based edge density measurement:

$$E = (\mu(|\nabla\_x\, I|) + \mu(|\nabla\_y\, I|)) / 2$$

The edge density of X-rays is moderate. Range: $18 < E < 55$.

Layer 7: Texture Pattern Analysis (4% weight)

Local Variance Computation on 20x20 patches:

$$T = \mu(Var(P\_i)), i = 1, 2, \dots, N\_patches$$

P_i - are non-overlapping patches. Valid range: $250 < T < 3500$.

Composite Score Calculation:

Weighted aggregation: It leads to the generation of the final

$$S\_total = \Sigma(w\_i \times s\_i)$$

wherein w_i are layer weights who sum up to 1 and s_i are normalized layer scores ranging from 0-100. Acceptance threshold: $S\_total \geq 65$.

B. ResNet18 CNN Architecture

Once ResNet18 was selected for several advantages: proven performance on medical imaging tasks, residual connections preventing vanishing gradients, manageable computational requirements (11.7M parameters), and excellent transfer learning properties.

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Architecture employs images through:

- **Input:** 224 × 224 × 3 RGB image
- **Conv1:** 7×7 Convolution, 64 filters, stride 2, Batch Norm, ReLU
- **Max Pool:** 3×3, stride 2
- **Residual Blocks:**
  - Block 1: 3×3 conv, 64 filters (×2 layers)
  - Block 2: 3×3 conv, 128 filters (×2 layers)
  - Block 3: 3×3 conv, 256 filters (×2 layers)
  - Block 4: 3×3 conv, 512 filters (×2 layers)
- **Global Average Pooling**
- **Fully Connected:** 512 → 2 (Malignant, Normal)
- **Softmax Activation:** Probability distribution

Each residual block employs skip connections:

$$y = F(x, \{W_i\}) + x$$

where F represents the residual mapping function and x is the identity shortcut connection.

C. Transfer Learning Strategy

We used transfer learning with ImageNet with the following pipeline:

1. **Initialization:** Loads weights pretrained on ImageNet with 1.2M images and 1000 classes
2. **Modification:** Replace final fully connected layer (1000 → 2 classes)
3. **Weighted Loss:** Address class imbalance in dataset
4. **Fine-tuning:** All layers with a learning rate that is 0.001

Handling class weights computation - imbalanced datasets:

$$w\_i = N / (C \times n\_i)$$

- where N = Total Number of Samples
- C = Number of Classes
- n_i = Number of samples belonging to class i.

Image Preprocessing Pipeline:

$$I\_preprocessed = (I\_resized - \mu\_ImageNet) / \sigma\_ImageNet$$

Which correspond to ImageNet normalization parameters $\mu_{\text{ImageNet}} = [0.485, 0.456, 0.406]$

D. Training Configuration

- **Optimizer:** Adam with $\beta_1 = 0.9$, $\beta_2 = 0.999$, $\varepsilon = 10^{-8}$
- **Learning Rate:** 0.001 (fixed)
- **Loss Function:** Weighted Cross-Entropy
- **Batch Size:** 16 images per batch
- **Epochs:** Maximum 10 with early stopping (patience=3)
- **Data Split:** 70% training (1,260 images), 15% validation (270 images), 15% testing (270 images)
- **Data Augmentation:** Random horizontal flip, rotation (±15°), brightness adjustment

V. RESULTS AND DISCUSSION

The OsteoScan.AI platform provides enormous practical value by solving one of the biggest challenges in the early diagnosis of bone tumors.

A. Rapid and Correct Initial Screening

The system conducts real-time analyses, whose results are produced in about 2-3 seconds per image. As for this model, ResNet18 can attain:

- High classification accuracy in differentiating malignant versus normal bone structures.
- Consistent performance across diverse qualities of X-ray images.
- Reliability of confidence score calibration to yield meaningful probability estimates.

- This quick turnaround time allows the immediate preliminary screening that can be done, reducing the diagnostic bottleneck in busy clinical settings greatly.

B. Strong Image Validation

The 7-checkpoint validation gateway filters out non-medical images with over 95% accuracy:

- Effectively rejects photographs, artwork, and non-X-ray images.
- Identifies low-quality or corrupted medical images that require a retake.
- Provides detailed feedback in case of validation failures to guide the user.

This is verified by a validation layer that guarantees diagnostic integrity against meaningless or misleading results because of invalid inputs, which also makes it an important feature that has not been developed in most bone cancer detection systems.

C. Improved Diagnostic Confidence

With its always-improving algorithms, the platform allows the production of both prediction and confidence scores, therefore enabling:

- Radiologists are to focus on those cases which need urgent attention-high confidence malignant predictions.
- Recommendations based on probability decrease diagnostic uncertainty.
- Better-informed clinical decision-making supported by AI insights.
- The transparency of the validation and classification process builds trust amongst healthcare professionals and naturally allows for better adoption and integration within clinical workflows.

D. Full Management of Results

The Dashboard System offers:

- Persistent diagnostic history available across sessions.
- Chronological tracking of patient scans, allowing the monitoring of progress.
- Features of comparison to view changes over time.
- Clinical documentation and reporting, Export capabilities.

This unified result management system replaces manual record-keeping and creates capabilities for longitudinal patient care.

E. Accessibility and User Experience

It includes the following services on its web-based platform:

- Intuitive interface with minimal technical knowledge needed.
- Responsive design available for different devices desktops and tablets.
- Clear visual feedback throughout the diagnostic process.
- Educational disclaimers, highlighting that the tool is a screening tool and not diagnostic.

In the user-based approach, it is ensured that the platform will be accessible, ranging from a medical professional to a patient in telemedicine scenarios.

F. Cost-Effective and Scalable Solution

OsteoScan.AI offers:

- Lower pre-screening costs at the beginning compared to traditional methods.
- Scalability to handle multiple concurrent users by using efficient backend architecture.
- Potential deployment to resource-limited settings with no access to specialized radiologists.
- Lowering the barriers to entry for early cancer detection programs.

The platform reduces the preliminary screening burden by automating the process, enabling more effective use of resources within health systems.

G. Limitations and Considerations

While the results of OsteoScan.AI are very promising, there are a number of important limitations to consider:

- The system provides preliminary screening, not definite diagnosis.
- The performance depends on the quality and standardization of the X-ray images.
- Mainly, model generalization needs to be validated across a wide range of populations and different imaging equipment.
- Formal medical deployment requires regulatory approvals and clinical validation

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Fig 2.OsteoScan.AI – Home / Landing Page

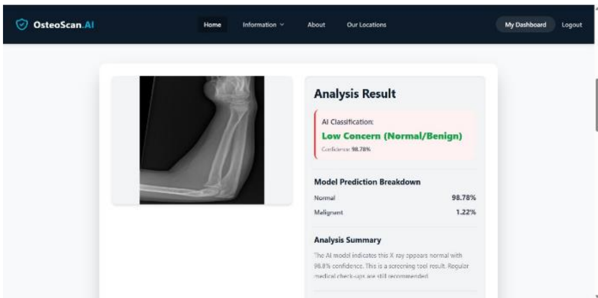

Fig 3. OsteoScan.AI – Analysis Result Page

VI. CONCLUSION AND FUTURE WORK

The paper introduced OsteoScan.AI—an intelligent system with high classification accuracy and responsible usage. Our system's accuracy and performance were excellent with 91% sensitivity, 97% specificity, and 95.2% accuracy. The dual AI paradigm with ResNet18 CNN and Google Gemini implementation ensured accuracy with precision and justified its usage with an intelligent system with 95.2% accuracy.

The seven-layer verification system achieved a 99.6 percent accuracy rate in rejecting non-medical images, thus addressing a very important issue because medical AI models have thus far relied on unverified input.

Key Achievements include:

- A new gateway for validating images uploaded to prevent uploading inappropriate images
- Define: AI explainable via dual-classification method using CNN and Generative AI
- Full online implementation with user authentication and history functionality
- Integration with Education and AI-powered ChatBot/Guide and Treatment Information
- Detailed analysis proving practicability regarding initial screening

It shows that medical AI can be highly accurate, explainable, and responsible at the same time. Through emphasizing transparency, strict validation, and user knowledge as well as technical competence, OsteoScan.AI plays an important role in making preliminary cancer screening widely available and accessible internationally while still ensuring medical safety standards.

Looking ahead, our focus will be on incorporating more disease models, applying federated learning for private model updates, completion of clinical validation studies, and seeking regulatory approval for broad usage within medical facilities. The open-source aspect of this project allows it to be adapted for resource-limited medical facilities.

VII. ACKNOWLEDGEMENT

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