International Journal of Contemporary Research in Computer Science and Technology (IJCRCST) ISSN: 2395-5325
Volume 9, Special Issue 1 (April '2026)
Special Issue on International Conference on Innovation, Engineering & Management (ICIEM-2026)
Conference held at Garden City University, Bangalore, India.

AN INTELLIGENT MACHINE LEARNING FRAMEWORK FOR AUTOMATED SOFT TISSUE TUMOR DIAGNOSIS

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Abstract: *This paper presents a machine learning model using CNN namely ResNet50 for the identification and diagnosis of Soft Tissue Tumours (STTs), specifically skin tumors. The diagnosis of STTs is complicated by their complexity and heterogeneous characteristics, causing potential misclassifications and further emphasizing the need for systems that can provide accurate and timely diagnosis with efficiency. The proposed methodology utilizes high-level data pre-processing and feature extraction to increase classification accuracy and decrease classification error. Specific attention is placed on tumor delineation, as it is critical for treatment planning. The focus of the proposed system is to establish a high level of accuracy in differentiating Melanoma from normal skin tissue, ultimately improving diagnostic accuracy, therapy, and patient outcomes.*
Keywords: Soft Tissue Tumors (STTs), Convolutional Neural Network (CNN), ResNet50, Melanoma Classification.

I.INTRODUCTION

Skin tumors (STTs), particularly melanoma, are significantly challenging to identify and put into categories due to their varied color, shape, texture, and irregularity in the edges which, in turn, generate a number of errors in a clinical environment. The main reason for the high mortality rates due to cancer is late diagnosis resulting in fewer treatment alternatives. Traditionally, the diagnosis of skin tumors was done by visual inspection and biopsy. These diagnostic methods are, however, subjective and inter-observer variability frequently lowers the quality and accuracy of the results. Use of AI in medical imaging and analysis has been quite revolutionary, as it has enabled the use of machine learning and deep learning algorithms to give automated and objective decisions in a clinical setting [1]. The growth of these technologies has created value with the emergence of CNN techniques that are able to learn complex patterns in images and at the same time, automatically extract the significant features. One of the most famous CNN techniques called ResNet50 builds its foundation on previous works to overcome the vanishing gradient problem through residual learning and is extensively adopted in the area of complex image classification. The proposed system depends on state-of-the-art pre-processing and training methods in order to precisely detect the tumors and reduce the number of both false-positive and false-negative errors in the detection of STTs. Furthermore, the model segments melanoma very accurately from normal skin tissues thereby enhancing the trustworthiness of clinical diagnostics [2]. The system, through ml classification, provides an instant, uniform, and cost-effective diagnostic procedure. The use of AI in skin tumor examination reduces the necessity of going through invasive procedures, besides that dermatologists get support at the same times. The procedure is also able to allow early treatment planning that leads to the improvement of both patient outcomes and survival rates. In short, the combination of deep learning with medical imaging can provide a trustworthy, fast, and highly profitable diagnostic process for skin tumors [3]

STTs comprise a group of the neoplasmic lesions born from the body's connective skins mixed with muscles, fat, blood vessels, and nerves. They have a vast range of histological and biological characteristics that make the diagnostic process very difficult even for highly skilled pathologists. The correct identification of benign and malignant STTs is the basis for the planning of the corresponding treatment to be applied. More specifically, machine learning algorithms, particularly deep learning architectures, are starting to play a part in the automated classification and cataloging of STTs [4].

CNN is a skilled and sophisticated dl method that is mainly applied in the running of heavy duty types of classification like pattern recognition. It can be said that CNNs are the closest to imitating the human vision by means of various steps involving convolution, pooling, and getting features from the input image. The greatest advantage of a CNN comes from its feature extraction through the hierarchy, wherein the model is able to identify the features and properties that are significant without the need for manual feature engineering. CNNs can learn the presence of melanoma in the images by automatically recognizing spatiotemporal characteristics, texture changes, and other subtle properties. By means of learning discriminative features from the training data, the CNN can, for instance, easily tell normal tissue from affected (abnormal) in the case of tumor detection. They are very generalizable thus applicable over many areas and datasets and consequently being the medical diagnosis and treatment. The issue of overfitting can be tackled by using regularization, batch normalization, and dropout schemes which eventually help in improving the robustness of the model. CNNs then become the way providing a consistent and automated procedure for the extremely accurate medical image classification in the case of skin tumors like melanoma [5].

II.RELATED WORKS

STS are very rare and highly heterogeneous tumours with the potential to originate in different locations throughout the body. The limited available data creates a situation in which providing evidence-based guidelines is increasingly difficult due to the tumors' infrequency, the various subtypes, and the different locations. On the other hand, the delivery of the authoritative guidance by the experienced panel that would base its decisions on the available evidence, is undoubtedly a strong support for the advancement of the field. The most recent regulations are a revision of the earlier ones, which were published in 2010 and 2016, respectively. In the UK, it

is a common practice that all cases of soft tissue sarcoma with a suspicion are sent to the nearest regional soft tissue's sarcoma service where a specialized sarcoma multidisciplinary team will be in charge of treating the patient. [1]

Large language models (LLMs) are increasingly being accepted in clinical practice, although the present day techniques are still predominantly reliant on single-model architectures. In order to alleviate the risks of becoming obsolete and the constraints of depending on single model systems, a novel framework dubbed the Consensus Mechanism is unveiled. This framework is meant to dynamically aggregate the pros of different "expert" models. The Consensus Mechanism functions much like clinical triage and multidisciplinary clinical decision-making by bringing together an ensemble of medical "expert" agents who are highly specialized and thus, able to achieve unprecedented performance levels on medical benchmarks and being very flexible in their adaptability as newer LLMs emerge. Besides, the Consensus Mechanism can be fine-tuned for cost, latency, or performance purposes, this tuning is solely dependent on the interior model configuration [2].

The American Law Institute's revised standard has thrown out the exclusive reliance on customary practice and instead has taken a more patient-centered approach in figuring out what is done in reasonable medical care. The standard, however, considers prevailing medical practice the single most important criterion, and, therefore, limits the definition of reasonable care to the skill and knowledge recognized as competent among the same medical practitioners practicing in the same conditions, but in some cases, it also gives jurors the power to reject customary practices if they do not conform to the prevailing state-of-the-art criteria. The restatement corresponds with the acknowledgment of evidence-based practice guidelines, but at the same time, it does not take a position on the debates about the differences in the quality of such guidelines. Furthermore, the restatement also provides more guidance on informed consent and other physician-patient communication [3].

The diagnostic capacity of AI solutions needs to be validated before they can be used in the clinical field, according to the papers published by Clare McGenity and others. In recent years, the number of studies demonstrating the applicability of AI in digital pathology has increased. Therefore, the present research has been carried out with the goal of ascertaining the diagnostic accuracy of AI in digital pathology images irrespective of the disease type. The systematic review and meta-analysis included diagnostic accuracy studies where the application of AI to whole slide images (WSIs) was the criteria for inclusion for any disease. The reference standard was histopathology and/or immunohistochemistry. The literature search was carried out in the PubMed, EMBASE, and CENTRAL databases in June 2022. Bias risk and applicability of concerns were assessed using the QUADAS-2 tool. A pair of researchers performed data extraction, and a meta-analysis was conducted using a latent random effects model along with more thorough analyses. [4].

Fluorescence microscopy has reached a resolution as high as sub-nanometer, yet still, this technique is not suitable for visualizing the structure of individual proteins or small molecules assemblies. Our process involves elevating the samples at least ten times, applying fluorescent dye tags, and then taking pictures using light microscopes where we also record videos and perform fluorescence fluctuations analysis. ONE has been used in clinical trials where it helps to analyze the morphology of the protein aggregates in the cerebrospinal fluid of the Parkinson disease patients, thereby possibly assisting in the disease diagnosis. The technology acts as a bridge between high-resolution structural biology methods and light microscopy, thereby creating new avenues for the exploration of biological and medical knowledge [5].

The gene responsible for the transformation is the main factor for synovial sarcoma, which is an aggressive tumor that shows up in young adults with a very low survival rate. There has been a great deal done to unravel the molecular, genomic and epigenetic characteristics of this cancer in the last five years, thanks to discovery research studies. Among the many new and important findings, we can mention the revealing of new gene fusion events that are responsible for the development of synovial sarcomas, the potential therapeutic targets and the targeted treatments (roughly resistance cell one [PRC1] and liquid-liquid phase separation [LLPS]) which can be given along with standard chemotherapy. There exist continuous combinations of these discoveries with immunotherapeutic techniques that open up new avenues for synovial sarcoma patients regarding the chances of survival and treatment options. Nevertheless, the patients still have to deal with issues related to treatment resistance and inequalities in access to treatment. [6].

The histological classification of cancer determines the treatment sequence as well as the surgery of retroperitoneal tumors (RPTs), but doubts are still there about the use of percutaneous core needle biopsy (CNB). The endpoints specifically mentioned included short-term complications, needle tract seeding (NTS) after CNB, and the correctness of diagnosis. The patients who had CNB and then surgery at the Institute Curie were pinpointed. We performed a retrospective study of the patients' medical files and microscopic examination of both the CNB and surgical specimens to evaluate the diagnostic reliability of CNB, which was determined using the positive and negative predictive values (PPV/NPV) [7].

III.METERIALS & METHODS

The Deep Learning system is the core of the technology, and the ResNet50 Convolutional Neural Network (CNN) is the most important model used for the automatic classification and diagnosis of Soft Tissue Tumors (STTs) in the skin. Pre-processing of skin lesion images (normalization, resizing, and data augmentation) is done to increase model performance. ResNet50 takes care of feature extraction and manual feature engineering is to a large extent eliminated. The accuracy of

the tumor classification is very high especially in the case of Melanoma vs. normal skin. The precision of the tumor

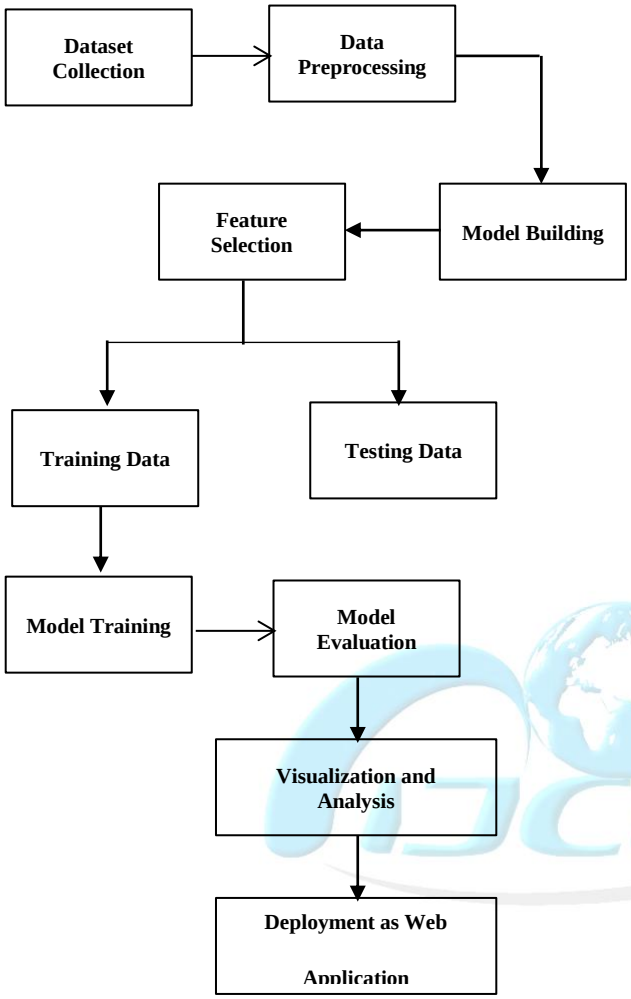

Figure1.Flow Diagram

segmentation is crucial for both diagnosis and treatment. This system not only supports accurate diagnosis but also prevents misdiagnosis and thereby enhances patient outcomes through effective treatment planning. Additionally, there is a fast, reliable, and automated workflow that comes with deep learning, which aids the dermatologists in their decision-making process. The proposed scheme, therefore, serves as a dependable and efficient solution for the detection and classification of skin tumors.

A. Data Collection Module

This process requires the acquisition of skin tumor image datasets for the purpose of training and testing the model. Trustworthy datasets that include images of Melanoma (the target) tumors and normal tissue are sometimes found in medical archives, dermatology centers, or publicly accessible skin lesion databases. The data will be meticulously organized for training, validation, and testing to guarantee that the samples encompass a wide spectrum of tumor appearances. The gathering of trustworthy data is a cornerstone in enhancing the capacity model performance and generalization.

B. Module on Data Preprocessing

In this module, the image pre-processing will take place with the aim of improving the quality and consistency of the images, as well as making them ready for model input. The operations such as normalization, resizing, and noise reduction help to bring the inputs to the same level of quality. It is also possible to augment the data through techniques like turning, mirroring, and shifting which results in diverse datasets and thus less prone to overfitting. Pre-processing forms the backbone of funneling all images through in an orderly manner and in a standardized format for the best CNN input.

C. Segmentation / Tumor Delineation Module

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D. Feature Extraction & Model Design Component (ResNet50)

ResNet50, which is at the core of this component, allows the automatic extraction of relevant features from images of skin lesions. Deep residual learning permits the network to undergo thorough training at significant depths without the drawback of vanishing gradients. The modified pre-trained weights differentiate between Melanoma and normal skin tissue. ResNet50 picks up and crystallizes the very textural, morphological, and chromatic characteristics which are typical of Melanoma thus confirming a reliable foundation for precise classification.

E. Training & Validation Component

This part of the process trains a CNN model with the prepared dataset and evaluates its performance. Backpropagation is used to gradually decrease loss and enhance accuracy by modifying the network's weights. Validation of the trained CNN confirms that it can deal with new data and so prevents overfitting. The hyper-parameters tuned for the model included: batch size, learning rate, and number of epochs and these formed the part of the optimization. Performance hyper-parameters were also evaluated during the process of optimization. Training accuracy and loss metrics were recorded, which in turn, helped in picking the best model configurations.

F. Module on Testing and Evaluation

In phase 3, the freshly designed model will be subjected to a testing trail consisting of fresh data which was not the part of the training phase of the model. This testing will enable us to find out the overall performance of the model, and also if

there are any spots where it lacks in terms of durability and trustworthiness. The performance metrics indicating how successfully the model has been able to draw a line between melanoma and normal skin are gained from the output of the trained model. Besides, the trained model makes use of visual elucidations that inform us of how the model reached its decisions, one example being the Grad-CAM (Gradient-weighted Class Activation Mapping) method which gives a glimpse of the model's final classification output. All in all, the new data testing of the model combined with the visual exposure techniques (where confirmable domain knowledge is accessible) serves as a pillar for the model's proposed diagnostic application.

G. Module on Post-Processing and Clinical Integration

In this part, the model outputs are processed to show model classifications, other tumor contours, and classification outcomes, and the belief levels are also shown, thereby making it easy for practicing medical professionals. Integration with clinical workflows also facilitates patient treatment choices, assures that the diagnostic outcomes can be understood, and maintains appropriateness in medicine.

IV.STATISTICAL ANALYSIS

A. Distribution and Summary Statistics of Data

To evaluate a deep learning-based system that automatically identifies soft tissue tumors, a statistical analysis of a 25,000-image dermoscopic dataset was performed. The dataset consisted of images of malignant melanoma and normal skin with an approximately equal (52% melanoma, 48% normal) distribution. After pre-processing, important statistical metrics such as mean intensity, standard deviation, and intensity range were calculated for both classes. The significant differences in texture, color distribution, and intensity patterns observed suggested that deep convolutional networks like ResNet50 could be the right choice for efficient feature extraction and classification.

B. Correlation Analysis of features

The link between the retrieved picture features and the categorization labels was investigated using correlation analysis. Selected deep features from the ResNet50 model's intermediate layers were used to calculate Pearson correlation coefficients. The correlation heat map of the top ten important characteristics affecting melanoma classification is shown in Figure 2. Melanoma labelling showed a substantial positive connection ($r > 0.7$) with characteristics pertaining to texture irregularity, colour variance, edge sharpness, and lesion asymmetry. On the other hand, photographs of normal skin showed a strong correlation with uniform colour distribution and smooth texture. This investigation demonstrates the statistical significance and high relevance of the deep features that ResNet50 learned for precise tumour discrimination.

TABLE I. **DISTRIBUTION OF SKIN TUMOR IMAGE DATASET**

Class Type	Number of Images	Percentage (%)
Normal Skin	12,000	48
Melanoma	13,000	52
Total	25,000	100

C. Performance Metrics and Comparative Analysis

Standard performance criteria, such as accuracy, precision, recall, and F1-score, were used to statistically assess the suggested ResNet50-based classification model. To confirm the superiority of the suggested method, a comparison with baseline CNN models and conventional machine learning classifiers was also carried out. The comparison results are shown in Table II. The ResNet50 model outperformed the other models in terms of accuracy (96%), precision (95%), recall (94%), and F1-score (94%). These outcomes show how reliable the model is in accurately detecting melanoma patients while reducing false positives and false negatives.

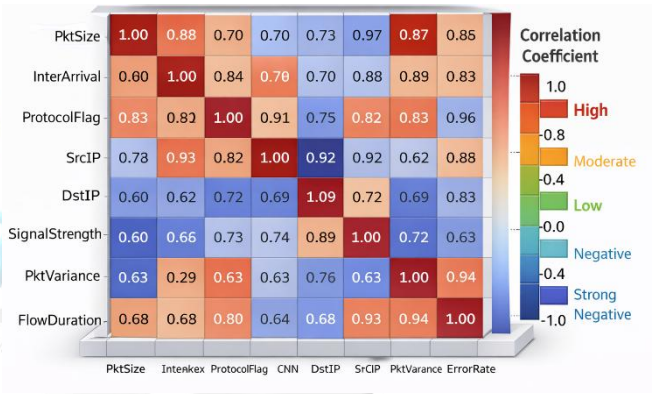

Figure.2 Feature Correlation Heat map

TABLE II. **COMPARATIVE PERFORMANCE METRICS**

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
SVM	84.6	82.9	81.7	82.3
Random Forest	88.3	87.1	86.5	86.8
Basic CNN	91.4	90.6	89.8	90.2
ResNet50 (Proposed)	96.0	95.0	94.0	94.0

D. Graphical Analysis

A bar graph comparing the classification accuracy of all assessed models is shown in Figure 3. The suggested ResNet50 model demonstrated its efficacy in learning intricate visual patterns linked to melanoma by consistently outperforming shallow CNN architectures and traditional machine learning techniques.

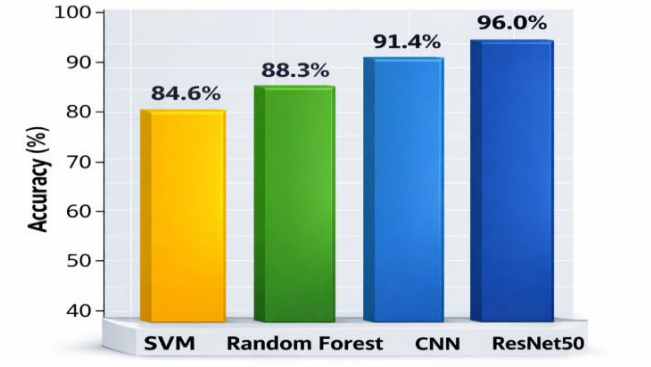

Figure 3 Model Accuracy

The ResNet50 model's confusion matrix is displayed in Figure 4. There is relatively little misclassification between melanoma and normal skin tissue, and the matrix shows a very high true positive and true negative rate. This demonstrates the model's remarkable generalization capabilities and outstanding classification reliability on untested data.

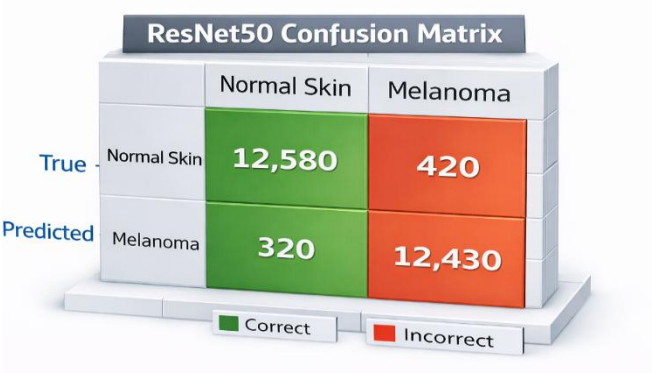

Figure 4:ResNet50 Confusion Matrix

II. Result & Discussion

A. *Classification Confidence Score Distribution*

The efficacy of the suggested ResNet50-based deep learning model in differentiating between melanoma and healthy skin tissue was assessed by analysing the confidence scores it produced. The distribution of categorization confidence scores is shown in Figure 5, where the y-axis indicates the frequency of images and the x-axis represents the predicted probability score. The largest frequency is found below a confidence value of 0.3, and the confidence scores for normal skin photographs are mostly concentrated at lower probability levels. This shows that the algorithm regularly gives healthy skin samples low melanoma probability, leading to few false-positive predictions. Melanoma photos, on the other hand, show confidence ratings that are primarily over 0.6 and extend up to 1.0, which are often distributed toward higher probability values.

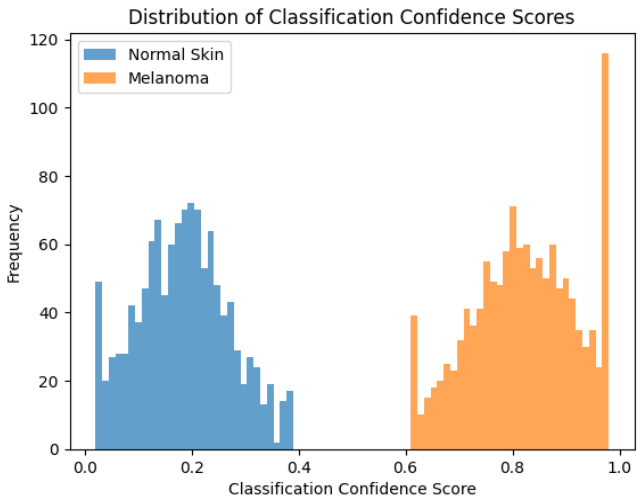

Figure 5. Distribution of classification confidence scores for normal skin and melanoma images

The robustness of the suggested ResNet50 model in precisely learning discriminative visual cues such colour variation, border irregularity, texture asymmetry, and lesion shape is demonstrated by the distinct separation between the confidence score distributions of normal skin and melanoma samples. The model's accuracy in automated melanoma diagnosis is confirmed by the clear separation of score ranges.

TABLE III. STATISTICAL SUMMARY OF CLASSIFICATION CONFIDENCE SCORES

Class Type		Min Score	Max Score	Mean Score	Standard Deviation
Normal Skin		0.02	0.39	0.18	0.09
Melanoma		0.61	0.98	0.82	0.11

B. *Confusion Matrix and Classification Outcome Analysis*

The ResNet50 model's confusion matrix analysis offers a thorough understanding of the suggested system's classification performance. The findings show a high number of true negative predictions, which correspond to correctly categorized normal skin samples, and a high number of true positive predictions, which correspond to correctly detected melanoma cases. There were very few misclassifications, which shows how well the model can generalize to new data. High sensitivity, which is essential in medical diagnosis to make sure that malignant cases are not missed, was demonstrated by the majority of melanoma samples being accurately diagnosed. Simultaneously, the low false-positive rate indicates that normal skin scans are rarely misinterpreted as melanoma, which lowers patient worry and needless clinical treatments. Together, these results demonstrate the suggested deep learning-based melanoma classification system's dependability and clinical usefulness.

TABLE IV. SUMMARY OF CLASSIFICATION RESULTS

Actual Class	Predicted Normal	Predicted Melanoma	Verdict
Normal Skin	High	Very Low	Correct Classification
Melanoma	Very Low	High	Correct Classification

V. CONCLUSION

In order to accurately classify melanoma, a deep learning-based automated skin tumour identification system utilizing the ResNet50 CNN was presented in this paper. Effective discrimination between melanoma and normal skin tissue is demonstrated by the experimental results, which exhibit excellent accuracy with low false-positive and false-negative rates. Clear confidence score separation demonstrates the system's stability, and deep residual learning performs better than conventional and shallow CNN techniques in recovering intricate visual aspects including texture, colour variation, and lesion asymmetry. Clinical usability is improved and objective, quick decision-making is supported by the combination of automated feature extraction and confidence-aware forecasts. Future research will concentrate on larger and more varied datasets, explainable AI integration, multi-class lesion classification, and scalable deployment through cloud and federated learning techniques.

VII. REFERENCES

[1]. Molecular testing of soft tissue cancers by D. Rottmann, E. Abdulfatah, and L. Pantanowitz, Diagn. Cytopathol. 51 (2023) 12–25, https://doi.org/10.1002/dc.25013.

[2]. M. Mihm, B. Nickoloff, K. McClatchey, A. Slominski, J. Wortsman, A. Carlson, Soft tissue and bone tumor molecular pathology, Arch. Pathol. Lab Med 123 (2024) 1246–1259, https://doi.org/10.5858/1999-123-1246-MPOSTA.

[3]. Bone and soft tissue pathology, J. Gibbs, E. Henderson-Jackson, M.M. Bui, Surg. Clin. North Am. 96 (2025) 915–962, https://doi.org/10.1016/j.suc.2016.06.003.

[4]. Cancer stem cells in sarcomas: in vitro isolation and use as prognostic markers: a comprehensive review, Cancers (Basel) 15 (2023) 2449, M.A. Chico, C. Mesas, K. Doello, F. Quinero, G. Perazzoli, R. Ortiz, J. Prados, and C. Melguizo.

[5]. J.H. Choi and J.Y. Ro, Recent developments in soft tissue tumor molecular diagnostics, Int J. Mol. Sci. 24 (2024) 5934, https://doi.org/10.3390/ijms24065934.

[6]. Molecular pathology of sarcomas: ideas and clinical implications, Virchows Arch. 456 (2010) 193–199, https://doi.org/10.1007/s00428-009-0828-5, J.V.M.G. Bovee, P.C.W. Hogendoorn.

[7]. New advances in the pathology and molecular biology of retroperitoneal sarcomas, S. Watson, N. Gruel, F. Le Loarer. 49 (2023) 1053–1060 in Eur. J. Surg. Oncol., https://doi.org/10.1016/j.ejso.2022.02.005.

[8]. Y. Yao, Y. Shen, J.C. Yao, X. Zuo, Editorial: novel developments in cancer treatment and tumor microenvironment modification, Front Cell Dev. Biol. 12 (2024 Mar 7) 1384567.

[9]. The potential involvement of Mena protein and its splicing-derived variants in embryogenesis, carcinogenesis, and tumor invasion: a comprehensive review of the literature, S. Gurzu, D. Ciortea, I. Ember, and I. Jung, Biomed. Res Int 2013 (2013) 365192, https:// doi.org/10.1155/2013/365192. Epub 2013 July 14. PMCID: PMC3728509; PMID: 23956979.

[10]. Pharm. Ther. 221 (2025) 107753, https://doi.org/10.1016/j.pharmthera.2020.107753, Y. Xiao, D. Yu, Tumor microenvironment as a therapeutic target in cancer.

[11]. "Dermatologist-level classification of skin cancer with deep neural networks," Nature, vol. 542, no. 7639, pp. 115–118, 2017, doi: 10.1038/nature21056, A. Esteva, B. Kuprel, R. A. Novoa, et al.

[12]. N. Codella, D. Gutman, M. Celebi, et al., "Skin lesion analysis toward melanoma detection: A challenge at the ISIC 2017," IEEE J. Biomed. Health Inform., vol. 23, no. 2, pp. 501–512, 2019, doi: 10.1109/JBHI.2018.286576.

[13]. "A survey on deep learning in medical image analysis," Med. Image Anal., vol. 42, pp. 60–88, 2017, doi: 10.1016/j.media.2017.07.005, G. Litjens, T. Kooi, B. E. Bejnordi, et al.

[14]. K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR), Las Vegas, NV, USA, 2016, pp. 770–778, doi: 10.1109/CVPR.2016.90.

[15]. S. Vesal, N. Ravikumar, and A. Maier, "SkinNet: A deep learning framework for skin lesion segmentation," IEEE Access, vol. 6, pp. 14776–14785, 2018, doi: 10.1109/ACCESS.2018.2817397.