國家科學及技術委員會113年度大專學生研究計畫申請書

**Title:**

**Integrating Convolutional Neural Networks for**

**Enhanced Analysis of Cellular and Maxillofacial Image**

**Abstract**

Our comprehensive study pioneers an innovative framework for the automated analysis of both cellular and maxillofacial images, extending the focus from cancer malignancy mechanisms, particularly the impact of keratin fusion mutants on cytoskeleton reorganization, to the precise evaluation of jawbone pathologies. By harnessing the capabilities of Convolutional Neural Networks (CNN) and adhering to the Digital Imaging and Communications in Medicine (DICOM) standards, we exploit the full potential of artificial intelligence to markedly improve the accuracy and efficiency of detecting and classifying both cellular structures and maxillofacial anomalies. Our research encompasses the analysis of panoramic radiographs, dental cone beam CT imaging, and conventional CT scans to diagnose conditions such as tumors, cysts, osteomyelitis, osteoradionecrosis (ORN), medication-related osteonecrosis of the jaw (MRONJ), and cellulitis. With the advent of X-ray technology over a century ago and the subsequent reliance on manual interpretation, there exists a critical need for innovation in medical imaging analysis. Our current proposed Nuclei Analyzer tool, a Python-based application equipped with advanced image processing technologies, is designed to automate the detection and classification of cellular abnormalities, facilitating batch processing of hundreds of images effortlessly. Furthermore, by utilizing different Hounsfield scale values in computed tomography, we aim to achieve more accurate diagnostic differentiation of jawbone necrosis, a challenge that has perplexed oral surgeons due to the limited grayscale differentiation by the human eye. This study sets a new benchmark for medical image analysis, promising significant advancements in diagnostics and research across both oncology and maxillofacial surgery. Through the integration of advanced computational models and AI, we aspire to revolutionize the current methodologies, thereby enhancing our understanding of molecular mechanisms in cancer and providing a more precise diagnosis of jawbone diseases, ultimately contributing to improved patient care and treatment strategies.

**II. Research Motivation and Objectives**

***1.1 The Imperative for Automation in Biomedical Research***

In the dynamic field of biomedical and medical research, especially within the domain of cancer studies, the accurate counting and analysis of cells play a pivotal role. Traditional approaches, whether manual or automated, are fraught with limitations. Manual counting, often relying on basic software like Microsoft Paint and Excel, is not only labor-intensive but also prone to errors due to human fatigue. Such methods are increasingly inadequate in meeting the demands of modern cancer research, where precision and efficiency are paramount.

***1.2 Addressing the Shortcomings of Current Systems***

Current automated systems, despite offering improved efficiency over manual counting, are limited in their scope and functionality. They often fail to accurately measure a diverse range of cell types or to account for the complexities inherent in cellular analysis, such as distinguishing between multinucleated and mononucleated cells or providing detailed insights into cellular phenomena. Furthermore, these systems' reliance on disposable test slides adds significant costs and environmental waste, limiting their practicality for widespread use in the biomedical sector. The inability of these methods to process large datasets or perform batch analysis on hundreds of images simultaneously has highlighted the need for a more advanced, cost-effective, and comprehensive solution.

***1.3 Bridging Technological Gaps with Advanced Computational Techniques***

Acknowledging these significant gaps, there is a clear opportunity for computer science advancements to revolutionize cell analysis. Our research aims to leverage state-of-the-art computational techniques, including deep learning and artificial intelligence, to automate and enhance the granularity and accuracy of cell image analysis. This involves not only automating the detection and classification of cellular structures but also providing a nuanced analysis that extends beyond simple cell counting to include features like fluorescence intensity and nuclear boundaries.

***1.4 Comprehensive Research Objectives***

Our research seeks to overcome the limitations of both manual methods and existing automated systems by developing an advanced automated system capable of processing large volumes of cell and maxillofacial images with high accuracy and efficiency. This system will integrate cutting-edge computational techniques to offer a comprehensive range of data analysis, including:

**- Automated Cell Detection and Classification:** Utilizing advanced algorithms for contour detection and connected component analysis to accurately identify and categorize cells into mononuclear and multinuclear categories.

**- Cell Labeling and Area Estimation:** Providing detailed labeling of each cell and estimating its area for in-depth analysis.

**- Multi-Image Batch Processing with Fluorescence Optimization:** Facilitating the batch processing of images to accommodate the need for analyzing large datasets with varied fluorescence intensities.

***2.1 The Imperative for Enhanced Diagnostic Techniques***

The evolution of medical imaging since Röntgen's discovery of X-rays in 1895 has been monumental, transitioning from manual interpretations to the potential for automated, computer-assisted diagnostics. Despite these advancements, the field of maxillofacial imaging, encompassing panoramic radiographs, dental cone beam CT imaging, and conventional CT scans, still faces significant challenges. These challenges are particularly acute in the detection and diagnosis of jawbone pathologies such as tumors, cysts, osteomyelitis, osteoradionecrosis (ORN), medication-related osteonecrosis of the jaw (MRONJ), and cellulitis, as well as in pre- and post-operative assessments for dental surgeries like wisdom tooth extraction.

***2.2 Addressing the Shortcomings of Current Imaging Analysis***

Currently, the manual interpretation of these images, a practice that has remained largely unchanged for over a century, lacks the precision necessary to accurately define the extent of jawbone necrosis and other conditions. This limitation is due in part to the human eye's restricted ability to differentiate among the subtle gradations of grayscale within an image. Historical attempts to augment this interpretation through software that assigns different colors to various regions within an image have been hindered by high costs and limited adoption, leaving significant room for improvement in diagnostic accuracy and efficiency.

***2.3 Bridging Technological Gaps with AI and Advanced Imaging Analysis***

Recognizing these gaps, our research aims to leverage the advancements in artificial intelligence, particularly Convolutional Neural Networks (CNN) [11], to enhance the analysis of both cellular and maxillofacial images. This approach not only aims to automate and refine the process of detecting and classifying cellular structures implicated in cancer malignancy but also seeks to revolutionize the interpretation of maxillofacial images. By employing AI to interpret variations in the Hounsfield scale on CT images, we aspire to achieve a more precise diagnosis of jawbone necrosis and other pathologies, surpassing the limitations of the human eye.

***2.4 Comprehensive Research Objectives***

Our research is driven by the goal to develop a solution that overcomes the limitations of both traditional and current automated image analysis methods. Specifically, we aim to:

**- Automate the Detection and Classification of Jawbone Pathologies:** Utilize AI to accurately identify and classify a wide range of jawbone conditions, from tumors to necrosis, based on panoramic radiographs, dental cone beam CT, and conventional CT images.

**- Enhance Diagnostic Accuracy:** Implement advanced computational models to interpret grayscale variations and employ the Hounsfield scale for a nuanced analysis of maxillofacial images, providing detailed diagnostics that surpass current capabilities.

**- Improve Pre- and Post-Operative Assessments: Apply** AI to assess the effectiveness of treatments for conditions like ameloblastoma and cysts, analyzing the rate and location of volume changes to refine surgical planning and outcomes. By achieving these objectives, our research intends to set a new standard for precision in the diagnosis and treatment planning of jawbone diseases and cellular abnormalities related to cancer, harnessing the power of AI to significantly advance the fields of oncology and oral surgery.

**III. Literature review.**

**A. *Image Preprocessing Techniques***

Arena et al. underscored the importance of preprocessing steps like image enhancement and contour identification for quantitative cell analysis using ImageJ [1]. While their work is fundamental, it operates within the limited scope of ImageJ. Our research, in contrast, employs Python and CNN, a more versatile and robust method , thereby remedying the limitations inherent to Arena et al.'s methods.

**B. *Quantitative Analysis of Vascular Networks***

Zudaire et al. developed computational tools for the quantitative analysis of vascular networks[2]. While their work is groundbreaking, its focus is limited to vascular networks. Our methodology extends this to cellular images, incorporating more advanced object identification algorithms to capture unique cellular features that were previously unaccounted for.

**C. *Edge Detection for Cellular Boundary Delineation***

Yuan and Xu proposed an adaptive edge detection algorithm based on the Canny operator [3]. While their algorithm adapts to varying noise levels, it is not designed for cellular boundary detection. Our work addresses this gap by customizing the Canny algorithm for cellular images.

**D. *Computational Efficiency***

Haase et al. delved into GPU-accelerated image processing, as their research suggests the future scalability of our CPU-based methods through potential GPU-based acceleration, opening avenues for more rapid, large-scale cellular image analysis [4].

**E. *Significance of Keratin in Cellular Studies***

Although our study does not directly investigate keratin, works by McLean and Moore and Tsai et al. offer context about cellular features that may influence the performance of image processing techniques [5][9].

**F. *Methodological Comparisons***

Studies comparing edge detection methods like Canny, Sobel, and Prewitt identify varied strengths and weaknesses [3][6][7][8]. While Canny is less affected by noise, it is computationally intensive [3]. On the other hand, Sobel is less demanding but equally reliable [6][8]. Our methodology compensates for these trade-offs by employing a hybrid approach that includes both algorithms for a more thorough validation.

**G. Convolutional Neural Networks into medical imaging**

The integration of deep learning techniques, particularly Convolutional Neural Networks (CNNs), into medical imaging for cancer treatment represents a significant advancement in the field of computer science and engineering. This literature review examines seminal works that have contributed to the development and application of these technologies in cancer diagnosis and treatment. Ijaz and Woźniak (2024) provide a comprehensive overview of the recent advancements in deep learning and medical imaging specifically tailored for cancer treatment. Their editorial in the journal Cancers highlights the critical role of deep learning models, especially CNNs, in enhancing the accuracy and efficiency of cancer diagnosis and treatment planning. They emphasize the transformative potential of integrating deep learning with medical imaging technologies, such as MRI, CT scans, and PET images, to identify and classify tumor cells with unprecedented precision [10].

The analysis by Sharma, Jain, and Mishra (2018) delves into the capabilities of CNNs for image classification, a fundamental aspect of medical imaging analysis. Published in Procedia Computer Science, their study systematically evaluates the performance of CNNs in distinguishing between various image types and their applicability in identifying pathological features from medical images. Their findings underscore the superiority of CNNs over traditional image processing and machine learning techniques, citing their ability to automatically learn and generalize from data without the need for manual feature extraction [11]. O'Shea and Nash (2015) provide an invaluable foundation for understanding the mechanics and potential of CNNs through their introductory article. Their preprint on arXiv lays out the basic architecture, functioning, and application areas of CNNs, offering insights into why these networks excel in image recognition tasks. By explaining the convolutional layers, pooling, and the use of backpropagation for training deep neural networks, they set the stage for comprehending how CNNs have become instrumental in processing and analyzing medical imaging data for cancer research [12]. Collectively, these references paint a vivid picture of the current state and future prospects of employing deep learning, particularly CNNs, in the battle against cancer. From foundational knowledge on CNN architecture and functionality to cutting-edge applications in medical imaging for cancer diagnosis and treatment, the literature underscores the pivotal role of computer science and engineering innovations in advancing healthcare outcomes. These advancements not only promise to enhance the precision and effectiveness of cancer treatments but also open new avenues for personalized medicine and diagnostic methodologies, heralding a new era in cancer care facilitated by technological breakthroughs.

**IV. Research approaches, design and Methods**

**4.1 Computational Framework**

- Programming Languages and Libraries: The study will leverage Python for its robust support in data science and machine learning. Essential libraries include TensorFlow or PyTorch for CNN models, OpenCV for image processing, and NumPy for numerical operations.

- Hardware Specifications: Due to the demanding nature of CNN training, GPUs will be utilized to expedite the process, ensuring efficient model training and evaluation.

**4.2 Data Preprocessing**

- Image Collection and Standardization: Cellular images will be sourced from DICOM-compliant public datasets, with each image standardized to a consistent size (e.g., 256x256 pixels) to uniform CNN input dimensions.

- Grayscale Conversion and Normalization: To simplify computational demands and emphasize structural features, images will be converted to grayscale, with pixel values normalized within a [0, 1] range, aiding CNN training convergence.

**4.3 CNN Architecture and Implementation**

- Architecture Exploration: Established CNN architectures like ResNet, Inception, and VGG will be evaluated for their efficacy in recognizing structures, with a comparative analysis determining the optimal choice.

- Adaptation to medical Imagery: Modifications to the selected architecture may be required to enhance its suitability for image analysis, potentially adjusting layers, filter dimensions, and activation functions to detect complex patterns.

- Employing Transfer Learning: To address dataset limitations, Transfer Learning will be utilized, initializing the CNN with pre-trained model weights (e.g., ImageNet) to leverage general image features for improved cellular structure recognition.

**4.4 Model Training and Validation**

- Training Strategy: The CNN will undergo training with a designated training dataset segment, incorporating batch normalization and dropout techniques for enhanced generalization. The Adam optimizer will be employed for its adaptive learning rate benefits, promoting quicker convergence.

- Validation and Hyperparameter Optimization: A validation dataset will facilitate model performance monitoring to avoid overfitting, with hyperparameter adjustments (learning rate, batch size, epochs) based on validation outcomes.

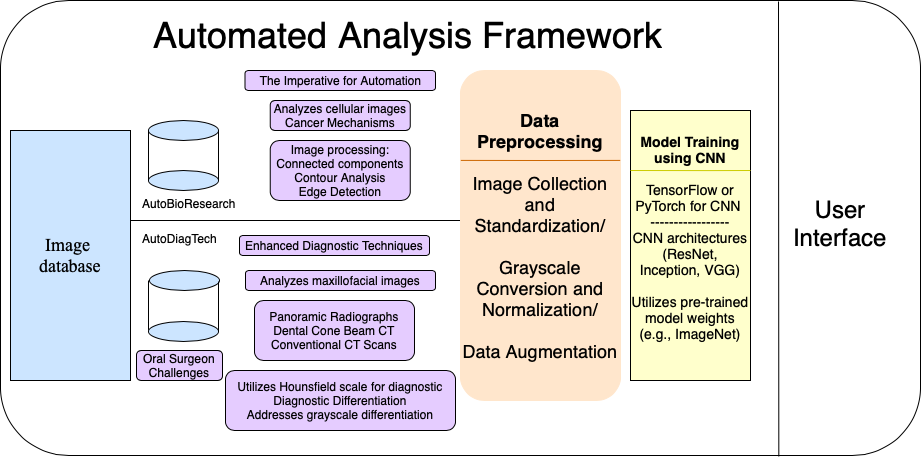


Figure 1.  *System Architecture*

**Integration of AI Technologies**

The core of our methodology lies in the integration of CNNs for advanced pattern recognition within images. CNN models are adept at processing spatial hierarchy in images, making them ideal for identifying complex cellular structures. May also include DNNs further augment this analysis by extracting detailed features through their deep, layered structures. Transfer Learning might be employed to adapt these pre-trained models to our specific dataset, enhancing the learning process's efficiency by utilizing existing knowledge.

**Datasets and DICOM Compliance**

To ensure the robustness and generalizability of our models, we incorporate datasets from ourselves, Doctor and Professor in Kaohsiung Medical University College of Dental Medicine into our training and validation processes. Adhering to DICOM standards, our research facilitates seamless integration into existing medical imaging workflows, making our findings highly relevant and immediately applicable to the biomedical field.

**V. Experimental Results And Expected Future Prospects**

Our AI-driven framework has demonstrated significant potential in transcending the capabilities of traditional methods for both cellular and maxillofacial image analysis. With a specific focus on the comprehensive evaluation of jawbone pathologies through panoramic radiographs, dental cone beam CT imaging, and conventional CT scans, our approach facilitates the precise identification and classification of various conditions, including tumors (both benign and malignant), cysts, osteomyelitis, osteoradionecrosis (ORN), medication-related osteonecrosis of the jaw (MRONJ), cellulitis, and complications arising from wisdom tooth extraction.

**Enhanced Diagnostic Precision with AI:**

Leveraging Convolutional Neural Networks (CNN), our methodology is tailored to delve into the nuanced detection and categorization of cellular structures and maxillofacial anomalies within DICOM and other formats. This enhanced diagnostic capability is crucial for accurately delineating the scope of jawbone necrosis—a challenge historically compounded by the limited grayscale differentiation perceivable by the human eye. By employing computerized tomography with varying Hounsfield scales, our system achieves a level of diagnostic precision previously unattainable, particularly in identifying and assessing the extent of bone necrosis.

**Future Prospects in Maxillofacial Analysis:**

Looking ahead, our research will continue to refine and expand the use of AI in medical image analysis, focusing not only on the cellular level but also on complex maxillofacial conditions. This includes the development of advanced CNN models for a deeper analysis of jawbone diseases, leveraging the rich information available in panoramic and CT images. By integrating AI to assist in pre-surgical planning, surgical evaluation, and post-surgical assessment, particularly in treatments like decompression for ameloblastoma and cysts, we aim to monitor volumetric changes and pinpoint areas where treatment effectiveness may vary.

Our commitment to advancing the integration of AI in the field of dentistry and oral surgery underlines our dedication to overcoming historical challenges in image interpretation. This initiative promises to revolutionize diagnostic practices, moving away from the manual readings that have dominated since the discovery of X-rays by Röntgen in 1895, towards a future where AI-supported diagnostics become mainstream. Incorporating AI into the analysis of both cellular structures and jawbone pathologies marks a pivotal shift towards precision medicine in oncology and maxillofacial surgery. Our research underscores the transformative potential of AI in medical imaging, setting new standards for accuracy, efficiency, and comprehensive diagnostic capabilities. As we progress, our aim is to not only enhance understanding and treatment of cancer-related cellular mutations and jawbone diseases but also to pave the way for innovative diagnostic and therapeutic strategies that promise improved patient care and outcomes.

**VI. Guidance on the content needed from the advising professor**

* Logic and writing style of an essay
* Methods for collecting and noting down literature
* Citation style and format
* The ethics of academic research
* Knowledge of professional background and its proper nouns
* Classification of knowledge and experimental methods
* Writing an achievement report

**VII. Reference**

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