MANIPAL ACADEMY *of* HIGHER EDUCATION

(Institution of Eminence Deemed to be University)

Development of Deep Learning Approach for Grading Squamous Cell Carcinoma from Histopathology Images

Mini-Project Synopsis

submitted to

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1. Introduction

Squamous Cell Carcinoma (SCC) is a common skin cancer that needs quick, accurate diagnosis for good treatment. Currently, doctors examine tissue samples under microscopes by hand, which is slow and different doctors might see different things. With more cancer cases every year, this method can't keep up.

We're developing a deep learning approach that can analyze histopathology images and determine if cancer is dangerous and grade it 1-3. The AI model spots the same warning signs doctors look for - abnormal cells and fast growth. Our goal is to create a reliable tool that helps doctors make faster, more accurate diagnoses for better patient care.

2. Problem Statement

Major problems with the current SCC diagnosis include its slowness, the fact that doctors may disagree on results, and the length of time patients must wait for answers. We must create a deep learning model that can swiftly examine histopathological pictures and make astute judgments as skilled medical professionals. It must appropriately classify severity, prevent false alarms, and identify cancer with accuracy. Above all, physicians must have enough faith in it to utilize it to diagnose patients more quickly and accurately.

3. Objectives

3.1 SCC Classification

- Build an AI model to identify if SCC is cancerous or not
- Use CNNs and pre-trained models like ResNet
- High accuracy in detecting cancer cases

3.2 SCC Grading

- Automatically grade SCC into levels 1-3 based on cancer aggressiveness
- Multi-class classification using deep learning models
- Accurate differentiation between all three grades

3.3 Image Integration

- Combine microscopy images with whole-slide images for better accuracy
- Use patch-based techniques and multi-input models
- Get both detailed cell information and broader tissue context

3.Literature Review

Paper Title	Authors	Dataset	Methods / Models Used	Key Findings / Results
Automated Grading of Lung Carcinoma Using Hybrid Deep Learning Approach	Jelena Musulin, Sandi Baressi Šegota	Lung carcinoma histopathology images	CNN-based deep learning	Multi-class grading accuracy: 87.2%, F1 score: 86.5%, Sensitivity: 86.8%, Specificity: 94.2%; robust grading of histopathology images.
LungCarcinoGrade-EffNetSVM: A Novel Approach to Lung Carcinoma Grading using EfficientNetB0 and SVM	Pragati Patharia, Prabira Kumar Sethy	Kaggle CT scan dataset: 1,000 images (338 Adenocarcinoma, 200 Large Cell Carcinoma, 260 SCC, 202 Normal)	EfficientNetB0 for feature extraction + SVM (one-vs-all ECOC strategy)	Accuracy: 86.88%, Sensitivity: 86.88%, Specificity: 95.63%, Precision: 87.06%, F1 score: 86.64%, MCC: 0.8257, Kappa: 0.65; fast computation (~9.3s/image)
Histopathology Image Grading of Lung Carcinoma using Deep Learning	Sethy P. K., Geetha Devi A., Padhan B., Behera S. K., Sreedhar S., Das K.	Histopathology images of lung carcinoma	Wavelet features + AlexNet	Accuracy: 88.5%, Sensitivity: 87%, Specificity: 93%; robust grading across multiple carcinoma types
Enhancing Oral Squamous Cell Carcinoma Detection using EfficientNetB3 from Histopathologic Images	Aditya Kumar, Leema Nelson	Oral SCC histopathology images	EfficientNetB3 CNN	High accuracy in oral SCC detection; EfficientNetB3 performed well
Histopathological Image based Oral Squamous Cell Carcinoma Classification Using Deep Network Fusion	Kumar Ankit, Vidit Kumar	Oral SCC histopathology images	Deep network fusion (multiple CNNs)	Improved classification accuracy by fusing multiple networks; effective for oral SCC grading

EsccNet: A Hybrid CNN and Transformers Model for Classification of Whole Slide Images of Esophageal SCC	Zhaoxin Kang, Mingqiu Chen, Hejun Zhang, Xiangwen Liao	Esophageal SCC whole slide images	Hybrid CNN + Transformer	Outperformed standard CNNs; effective for whole slide image classification
Squamous Cell Carcinoma Margin Classification Using Vision Transformers from Digital Histopathology Images	So-Yun Park, Gelan Ayana, Se-woon Choe	828 histopathological images (345 margin-negative, 483 margin-positive) from Jimma University Medical Center	Vision Transformer models (ViT-B16, ViT-B32, ViT-L32) + Dense & normalization layers; compared with ResNet50	ViT-B16 achieved 0.906 accuracy & 0.905 AUC, outperforming CNN; highlights ViTs' superiority
Classification of Non-Small Cell Lung Cancer Using Deep Learning	Lathakumari K. R., Ramachandra A. C., Avanthi U. C., Basil Ronald C., Bhavatharani T.	Kaggle CT scan dataset: 1,000 images (Adenocarcinoma, SCC, Large Cell Carcinoma, Normal)	EfficientNetB2 (342-layer CNN) + preprocessing + Softmax	Training accuracy: 95%, Testing accuracy: 83%; strong performance but dataset limitation noted
Multi-Teacher Knowledge Distillation with Reinforcement Learning for Visual Recognition	Chuanguang Yang, Xinqiang Yu, Han Yang, Zhulin An, Chengqing Yu, Libo Huang, Yongjun Xu	Standard visual recognition datasets	Multi-teacher KD with reinforcement learning to weight teachers	Outperforms traditional KD by dynamically adjusting teacher weights; improves recognition accuracy
Advancing Trans-Domain Classification With Knowledge Distillation: Bridging LIDAR and Image Data	J. Eduardo Ortíz, W. Creixell	nuScenes dataset (LIDAR + camera)	Transformer-based KD transferring knowledge from image → LIDAR	Improved accuracy & inference speed vs PointNet++; efficient alternative to sensor fusion
Multiple Teachers Are Beneficial: A Lightweight and Noise-Resistant Student Model for Point-of-Care Imaging Classification	Yucheng Song, Anqi Song, Jincan Wang, Yifan Ge, Lifeng Li	ISIC, BUSI, Dermnet datasets	Lightweight Shift MLP student + multi-teacher KD; supervised + distillation + consistency losses	Strong performance while reducing parameters 38× and FLOPs 11×; robust for noisy, resource-constrained imaging
Deep Learning for Clinical Image Analyses in Oral Squamous Cell Carcinoma	Chui Shan Chu, BSc, MMedSc1; Nikki P. Lee, PhD2; Joshua W. K. Ho, PhD3,4	Histopathology images used form SUM hospitals,clinical oral images	VGGnet, ResNet, Dense net Efficient net	Pathological images:77.9%-97.5% Accuracy Radiolographic images:76%
Histopathology-based diagnosis of oral squamous cell carcinoma using deep learning	S.Y. Yang, S.H., and W. Liao	Total images of 2,025 images were collected from the pathologiest	CNN based model was used in this paper frame work used here is binary classification	sensitivity was 0.98,f1 score is said as 0.951 Post predictive value:0.924

Colorectal cancer detection with enhanced precision using a hybrid supervised and unsupervised learning approach	Akella S. Narasimha Raju, K. Venkatesh, Ranjith Kumar Gatla, Eswara Prasad Konakalla, Marwa M. Eid, Nataliia Titova, Sherif S. M. Ghoneim, Ramy N. R. Ghaly	CVC-ClinicDB (1,650 colonoscopy images of polyps & non-polyps; preprocessing and augmentation applied)	CNN ensembles (ADa-22 and AD-22) for feature extraction, Transformer for context, SVM for classification, and K-means with bounding boxes for segmentation and interpretability.	The best model (AD-22 + Transformer + SVM) reached 99% test accuracy, AUC 0.99, with strong recall for both polyps and non-polyps. K-means segmentation (silhouette up to **0.73**) added interpretability alongside high accuracy.
A coded knowledge distillation framework for image classification based on adaptive JPEG encoding	Ahmed H. Salamah, Shayan Mohajer Hamidi, En-Hui Yang	CIFAR-10, CIFAR-100, ImageNet	Coded Knowledge Distillation (CKD) with adaptive JPEG compression before teacher model; compared with standard KD and other variants (FitNet, AT, RKD, SP, CC)	Adaptive compression produces softer teacher outputs, reduces over-confidence, improves student accuracy consistently across benchmarks with low computational cost

4. System Requirements

4.1 Hardware Requirement

- **Graphics Card**: You will need a decent GPU to train AI models and handle large medical images
- **Processor**: A solid CPU for general computing tasks
- **Memory**: Enough RAM to work with high-resolution images smoothly
- **Storage**: Fast storage for quick file access

4.2 Software Requirement

- **Operating System**: Ubuntu 20.04+ or Windows 10/11
- **Programming**: Python 3.8+ for AI development
- **AI Frameworks**: TensorFlow/Keras or PyTorch for building neural networks
- **Code Editor**: Google Colab
- **Data Tools**: NumPy and Pandas for data work
- **Visualization**: Matplotlib, Seaborn, and TensorBoard/WandB for tracking progress

5. Architecture

5.1 System Overview

- **Input Acquisition**
    - **Microscopy Images:** High-resolution tissue images providing cellular detail. **Whole Slide Images :** Large-scale scans divided into smaller patches.
- **Preprocessing Module**
    - **Normalization**: Standardizes color intensity and normalization across images to account for staining variation.
    - **Tiling (for WSIs)**: Splits WSIs into manageable patches.
    - **Data Augmentation**: Rotation, flipping, scaling, cropping to improve generalization.
- **Feature Extraction Module**
    - **Convolutional Neural Network (CNN)**: Models like ResNet/EfficientNet capture cancer-related patterns.
    - **Transformer-based Models**: Vision Transformers handle long-range dependencies.
- **Aggregation & Attention Mechanism**
    - **Patch Aggregation**: Combines patch features for global slide representation.
    - **Attention Mechanism**: Focuses on critical tumor regions for higher accuracy.
- **Classification and Grading Module**
    - **SCC Detection**:Classifies images as SCC or non-SCC.
    - **Grading**:Assigns Grade 1–3 based on severity.
- **Post-processing & Visualization Module**
    - **Refinement**:Uses thresholds and rules to finalize predictions.
    - **Visualization**: Heatmaps/overlays highlight key cancer regions for interpretability.

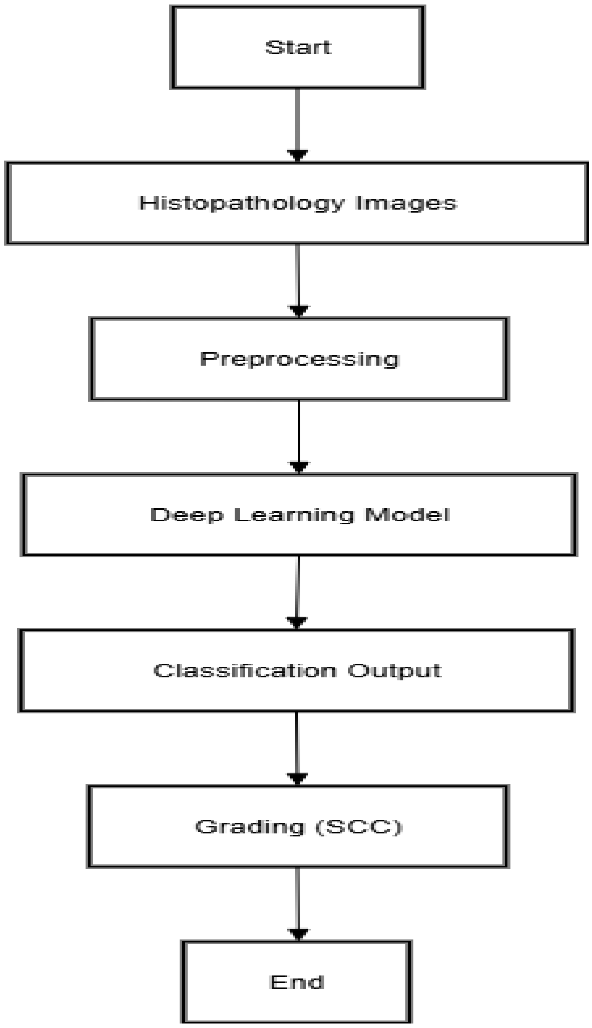

Fig 4.1: SCC Grading Block Diagram

6. Real-World Applications

6.1. Early Cancer Detection

- Detects squamous cell carcinoma in tissue samples before it has spread
- Earlier detection results in improved treatment and greater survival rates

6.2. Planning of Personalized Treatment

- Grades tumors based on how aggressive they look under the microscope
- Helps doctors tailor treatment plans to each patient's specific cancer type

6.3. Making Pathology Labs More Efficient

- Automates routine analysis tasks, freeing up pathologists for complex cases

- Faster diagnoses and reduced workload for overloaded medical labs

6.4. Supporting Medical Decision-Making

- Provides a reliable second opinion for challenging or uncertain cases
- Gives doctors more confidence in their diagnoses and reduces mistakes

6.5. Consistent Care Everywhere

- Provides the same diagnostic quality wherever you go
- All patients receive consistent, trustworthy cancer screening no matter where they are

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