

SELF DECLARATION

I hereby declare that the project work entitled “**SICKLE CELL ANEMIA CLASSIFICATION USING DEEP LEARNING**” is a genuine work carried out by me in B.Tech. (C.S.E.) at SRKR Engineering College(A), Bhimavaram, and has not been submitted either in part or full for the award of any other degree or diploma in any other institute or University.

Goriparthi Jahnavi

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ABSTRACT

Sickle Cell Anemia (SCA) is a severe hereditary blood disorder that changes the shape of red blood cells to that of an elongated disk, drastically reducing their ability to transport oxygen. Because of this mis-shaping, blood flow is frequently blocked, leading to chronic pain and damage to organs as well as other life-threatening complications. Early and accurate diagnosis is indispensable to effectively ameliorate the consequences of SCA for patients. New technologies, such as automatic deep learning (Automated DL) and transformer-based models allow us to accurately identify SCA from microscopic blood smear images.

Essential preprocessing techniques were applied first. These involved images resizing normalization and augmentation of image quality an essential factor for labeling data sets after all! In the category of classic DL architecture, InceptionV3 performed best and was most consistent, with the highest accuracy for classification. Apart from CNN, however, VGG16 Mobile Net and ResNet also showed moderate results. Defining this as the point to set the system's starting point, will give us a strong line for comparison.

In order to achieve more sensitive detection of delicate cellular features, we tried several transformer-based architectures such as MaxVit, CoAtNet, DeiT-3, and Mobile SAM. The results clearly indicated that our Mobile SAM model, based on self-attention and neat tricks, learned better distinguishing features from complex image patterns than previous models regardless of index value or dimensionality From this starting point, we designed a hybrid model that combined InceptionV3 for deep feature extraction at different levels of hierarchy with Mobile SAM for attention enhancement that is aware contextually.

This hybrid model was particularly striking, exhibiting an accuracy rate of 92.5 percent and reducing loss to 0.406. The statute also posted strong sensitivity (Correctly identified sufferers of sickle cell) and specificity (Rightly identified non-sicklers).

These results confirm the effectiveness of combining CNNs with attention-based structures in medical image processing. In addition, our work confirms the role of deep learning and mixed algorithms in building robust yet scalable diagnostic tools. The model design advocated here not only ensures high levels of accuracy in detection but also serves as a realistic basis for putting AI into real-world practice in hematology.

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LIST OF SYMBOLS

SYMBOL	DEFINITION
SCA	Sickle Cell Anemia
SCD	Sickle Cell Disease
DL	Deep Learning
CPU	Central Processing Unit
SVM	Support Vector Machine
CNN	Convolutional Neural Network
Inception V3	Inception Version 3
ResNet	Residual Networks
MobileNet	Mobile Neural Network
VGG16	Visual Geometry Group 16-layer Network
MaxViT	Maximal Vision Transformer
Mobile SAM	Mobile Segment Anything Model
CoAtNet	Convolutional Attention Network
DeiT-3	Data-efficient Image Transformer 3

