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RESEARCH ARTICLE

LC-DCNN: CLASSIFICATION OF LIVER CANCER VIA DEEP LEARNING BASED DILATED ATTENTION CONVOLUTIONAL NEURAL NETWORK

Buchhi Ramakantha Reddy [1, *], and S. Prince Samuel [2]

[1]Associate Professor, Department of Computer Science and Engineering (AI ML), Sri Venkateswara College of Engineering, JNTU ANANTAPUR, Tirupati, Tamil Nadu, India

[2] Assistant Professor, Department of Biomedical Engineering, SNS College of Technology, Coimbatore, Tamil Nadu, India

[*]*Corresponding e-mail: ramakanthareddy@gmail.com*

Abstract – Liver cancer (LC) occur when normal cells develop aberrant DNA alterations and reproduce uncontrollably. Patients with cirrhosis, hepatitis B or C, or both have an increased risk of developing the progressing stage of cancer. The radiologists spend more time for detecting the LC when analysing with traditional methods. Early detection of LC can help doctors and radiation therapists identify the tumours. However, manual identification of LC is time-intensive and challenging process in the current scenario. In this work, an automated deep learning-based LC-DCNN model is designed to classify the LC in its initial phase. At first, the CT scans are gathered from the publicly available LiTS database and these gathered images are pre-processed using Gaussian filter is used for reducing the noises and to smoothen the edges. The liver region is segmented using Enhanced otsu (EM) method is utilized to segment the liver region separately from the pre-processed input images. Afterwards, Dilated Convolutional Neural Network (DCNN) with the attention block is employed for classifying the LC into tri-classes such as normal controls (NC), hepatocellular carcinoma (HCC) and cholangiocarcinoma (CC) cases based on the extracted features. The effectiveness of the proposed LC-DCNN is evaluated using the attributes viz., accuracy, sensitivity, precision, specificity, and F1-score values are computed as classification results. The experimental fallouts disclose that the DA-CNN attains an accuracy range of 98.20%. Moreover, the proposed DA-CNN advances the overall accuracy by 3.25%, 5.29%, and 0.99% better than Optimised GAN, OPBS-SSHC, HFCNN respectively.

***Keywords** – Liver cancer, Deep learning, CT images, Attention block, Enhanced otsu method.*

1. INTRODUCTION

Liver cancer (LC) is a malicious tumour that originates in the liver cells, medically referred to as hepatocellular carcinoma (HCC). Globally, LC is the prevalent and aggressive forms of cancer with a high mortality rate [1]. LC can be caused by chronic liver illnesses like hepatitis B or C infection, cirrhosis, heavy liquor consumption, exposure to aflatoxins, and certain genetic conditions [2,3]. In most cases, LC progresses silently, with symptoms frequently appearing only after the condition has progressed. In addition to fatigue, jaundice, and unexplained weight loss, stomach pain is another symptom. LC poses significant challenges due to its insidious onset, complex etiology, and limited treatment options, resulting in a high mortality rate [4,5].

Regular screenings and timely medical intervention are essential for early detection, which improves prognosis and increases the efficacy of existing treatment modalities. Diagnostic procedures often include imaging studies, blood testing, and occasionally a liver biopsy [6,7]. A patient may be treated with chemotherapy, radiation therapy, targeted therapy, surgery, or a liver transplant, depending on the stage of the malignancy [8]. The prognosis for LC is still poor despite improvements in treatment options, underscoring the vital significance of early intervention, routine screening, and preventative measures. The precision and efficiency of traditional diagnostic procedures such as MRI, CT and US imaging techniques are limited which frequently results in incorrect or delayed diagnosis [9,10].

Machine learning (ML) [11] and Deep learning (DL) [12] has emerged as a promising tool in medical imaging analysis, including the identification and diagnosis of LC. DL algorithms [13] effectively extract complex patterns and characteristics from vast amounts of medical imaging data, enabling them to detect subtle abnormalities indicative of LC with high accuracy and efficiency [14]. In this research, we explore the application of DL technique for the detection of LC using CT scan images. The main contributions of the work are summarised as:

- Initially, the CT scan images are gathered and processed by using Gaussian filter to reduce the noises and to smoothen the edges.
- An EM method is used to segment the liver region separately from the pre-processed CT images.
- Afterwards, DCNN induced with attention block is employed for classifying the liver cancer into NC, HCC and CC cases.
- The proposed LC-DCNN model efficiency is assessed using the attributes like accuracy, sensitivity, specificity, precision and F1 score for computing the classification results.

The Organization of the paper was scheduled as follows: Section 2 presents the summary of the literature followed by an extensive description of the proposed LC-DCNN methodology for LC classification in Section 3, results and discussion presented in Section 4, and Section 5 holds conclusion part.

2. LITERATURE REVIEW

In this section, the challenges associated with traditional methods and the usage of DL-based approaches was discussed in overcoming these challenges. Furthermore, the recent advancements and existing architectures in DL was reviewed for LC recognition, emphasizing their strengths and limitations in this section.

In 2022, Amin et al., devised [15] an optimized GAN for image synthesis, followed by localization using an improved model. Deep features from pre-tuned ResNet50 were inputted to the YOLO-v3 model. Segmentation employs a pre-trained InceptionResNetV2 model for Deeplabv3, fine-tuned with annotated masks. Experimental findings demonstrate a testing accuracy exceeding 95%.

In 2021 Kushnure, and Talbar putforward [16] a multi-scale approach that augmented the CNN's receptive field by incorporating multi-scale features, thereby capturing both local and global characteristics at a better granularity. Experimental results demonstrated improved efficiency of the system on the 3Dircadb database. Specifically, the method attained a dice score of 97.1% and 84.1% for LC detection.

In 2021 V. Hemalatha et al., [17] introduced a method that combines Region of Interest (ROI) extraction with the Adaptive WS technique for the detection of LC. This methodology incorporates ANN techniques for denoising, scanning, extraction, and segmentation. To recognize LC within real-time datasets, a feed-forward neural network was employed. Subsequently, the extraction of features was conducted using GLCM techniques.

In 2020 B. Sakthisaravanan et al. [18] designed an OPBS-SSHC approach for liver tumor identification, integrating segmentation and similarity-based hybrid classification. Noise removal during preprocessing was followed by edge enhancement using a frequency-centered sharpening technique. Subsequently, the SSHC model classified extracted features, achieving a superior accuracy of 93% compared to other systems.

In 2020 Dong, et al., designed [19] suggested a Hybridized Fully CNN for the segmentation of LC. The suggested method combines residual connections and pre-trained parameters with the effectively extracted feature information from Inception. This DL system illustrates the idea of illuminating certain decision-making steps in a deep neural network was trained extensively. From the analysis the suggested HFCNN attains the accuracy of 97.22% for 50 epochs.

In 2019 Hamm., et al., [20] devised custom convolutional neural network (CNN) through iterative refinement of the network architecture and training samples. Monte-Carlo cross-validation was employed during this method development process. Upon completion of model engineering, the classification accuracy of the finalized CNN reached 92.0%.

According to the literature review, the existence of noise abnormalities in CT scans poses challenges for liver segmentation. Given the intricate structure of the liver, many clinical decision support schemes, particularly those employing ML techniques, rely heavily on segmentation. Utilizing CT scan images for automated LC diagnosis is pivotal due to potential variations in structural alterations among patients. To address these problems, a novel LC-DCNN model utilizing CT images for early-stage LC identification has been proposed. This study introduces a region-based segmentation technique for recognising the LC area, ultimately aiming to design an efficient approach for LC categorization.

3. PROPOSED METHOD

This proposed section presents a novel DL-based LC-DCNN model to identify the LC cases from the available LiTS dataset. The overall workflow of the suggested LC identification method is displayed in figure.1.

3.1 Dataset description

This study utilizes the common LiTS dataset from [21] which comprising 194 CT scans containing lesions and 201 liver CT images. The diverse and varied characteristics of tumor lesions pose significant challenges for automated segmentation. The goal is to design automated segmentation approaches that can detect liver tumors in contrast-enhanced CT scans. The overall data is composed of a training set of 130 CT scans and a test set of 70 CT scans.. This task is coordinated with MICCAI 2017 and ISBI 2017.

3.2 Gaussian filter

The Pre-processing stage of medical images is important for improving the quality and interpretability of diagnostic results. The Gaussian filter is a linear filter which reduces noise and smooths images while maintaining important features. In the image, each pixel is subjected to a weighted average determined by a Gaussian function. A Gaussian function smoothest the image by giving more weight to pixels near the center of the filter window. This gaussian function is mathematically determined as,

$$G(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \quad (1)$$

Where $G(x,y)$ represents the Gaussian kernel, σ is the standard deviation, which controls the extent of smoothing provided by gaussian distribution, x and y are the spatial co-ordinates of the filter. In the next step, the input is convolved by a Gaussian filter to create the smoothed output. Based on the specific requirements, the kernel size and σ value was changed in the properties of the input images.

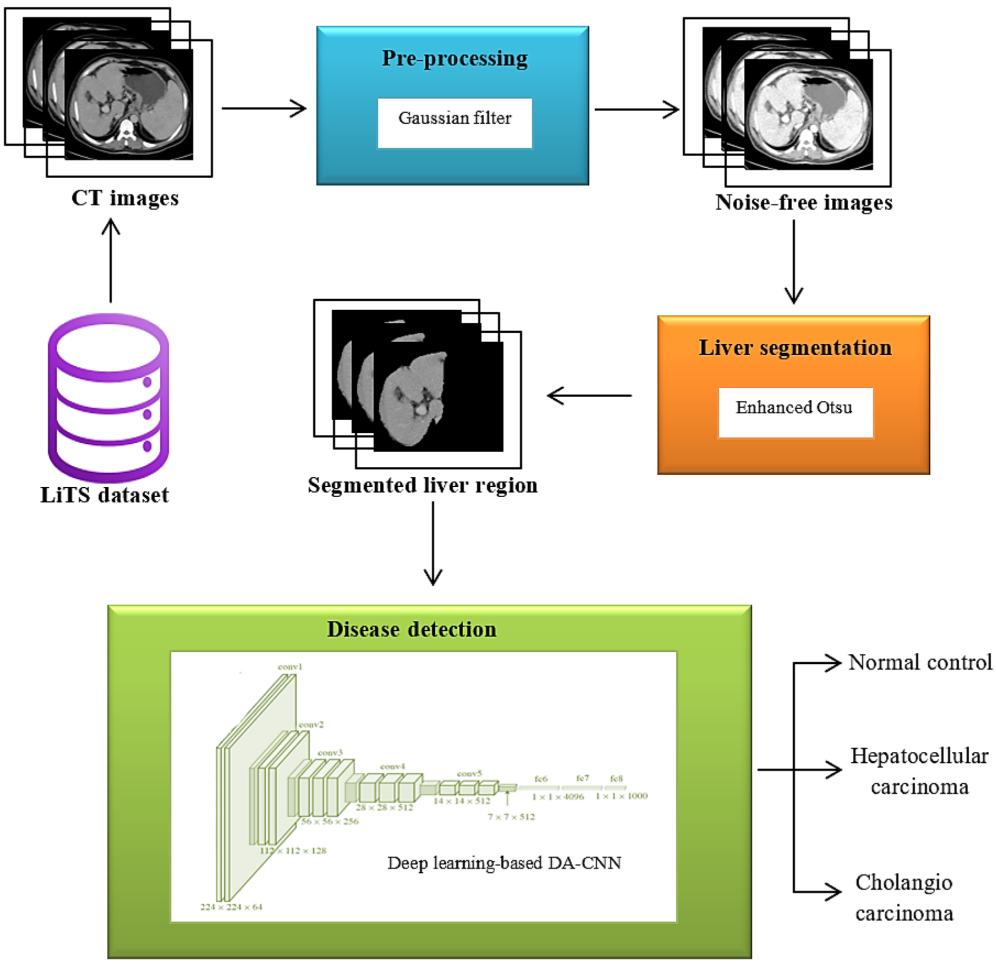

Figure 1. The outline of the overall proposed LC-DCNN identification model

3.3 *Enhanced otsu method*

After filtering the image is subjected to a segmentation process, where the Enhanced otsu (EM) method is used for liver region segmentation. In this EM method, the discriminate analysis is used where the threshold value is set in retaining the pixels of the image when it is split into two such classes. C_1 and C_2, where $C_1 = \{0,1,2,\ldots t\}$ and $C2 = \{t+1, t+2, \ldots M-1\}$.The values corresponding to the class variance (within and in between) and the total variance are analysed in such a manner that to determine very effectively.

$$\Gamma = \sum_{\tau=0}^{M-1} \Gamma_i + \sum_{\sigma=1}^{N} T(n-1) \quad (2)$$

As per the condition, Pi is represented as the possibility of incidence of the modified grey level i. Otsu method used here will analyse the becoming aspects of the threshold values in order to analyse the obtained optimal values for the given image. The threshold value t of the given image will indicate the $C_1 = \{0,1,2,\ldots t\} and C2 = \{t+1, t+2, \ldots M-1)$. This is mathematically expressed as

$$\Gamma_{rs}(x) = \sum_{x=1}^{\infty} x(k).\frac{1}{\vartheta\sqrt{\sigma_x}}.\ exp\left[\frac{P_k}{2\sigma_x}\right] \quad (3)$$

The maximum value of the segmented image is used for evaluating the classes C1 and C2 in a separate process. This could be possible by fixing the original image to a certain extent in combination with the histogram equalization methods. The Corresponding equation representing the output value of segmentation is given as

$$X_G[P]_\alpha = \sum_{x,y\in\gamma} \Gamma_{rs}(x-y) + \frac{1}{R_p}\sum_{x.y}[P_x - P_y] \quad (4)$$

Here the lower bound is gathered by the possibility of considering the original image with a single grey Constraints from the lower bound and the upper bound in correlation with the images which is of different values.

3.4 *Dilated Attention-Convolutional Neural Network*

In DA-CNN, an attention block is integrated with DCNN for focusing the most relevant features while extracting for better classification results. Dilated convolutions enable a larger responsive region without adding more parameters. In liver CT images, DCNN excel at extracting these features by effectively capturing spatial relationships at different scales. By employing dilated convolutions with increasing dilation rates across multiple layers, the network can aggregate information from a varied range of spatial contexts, enabling it to discern subtle patterns indicative of liver lesions. In particular, the convolution process can be expressed as follows assuming input features X and a filter K as follows

$$(X_P * F_K)(l,k) = \sum_n \sum_m X_P\,(l - n * d_r\,, k - m * d_r) F_K(n,m) \quad (5)$$

Where, d_r be the dilated rate and F_{K1} filter captures larger patterns because it encompasses a broader range of features than the F_{K2} filter, which operates as a standard convolutional filter and is ideal for extracting few patterns.

$$U = n + (n-1) \times (D_i - 1) \quad (6)$$

The image integrating matrix U is continually scanned by the convolution kernel. Dilated convolutions increase the interval of scanning features and add a few areas among convolution kernels. The effective height of the convolution kernel, essentially determines numerical value of U as in equation (6), assuming that the dilation rate is Di.

$$c_n = X(W' \times s^k_{i:i+u-1} + d) \quad (7)$$

The feature c_n is retrieved and expressed as follows after the convolution procedure.

$$Q_i = K_m = V_m = o_p \quad (8)$$

The attention block shows the effective concentration on appropriate spatial data, improved feature extraction, and the capacity to adaptively adjust to various components of the input data for quality performance. To learn a spatial attention map W_m and then multiply it by the associated spatial locations.

$$W_m(C) = sigmoid\big(c^k([Avgpool(C); Maxpool\ (C)])\big) \quad (9)$$

where c^k represents a standard convolution process with kernel size k. This module produces a spatial attention map by considering the importance of each spatial position within the response maps. The spatial-attention method is defined as,

$$M_s(f) = \sigma(f\left(f_j\left(f_{avg} + f_{max}\right)\right)) \quad (10)$$

where f_j is the join operation, f_{avg} indicates global average pooling and f_{max} global max pooling features respectively. In order to calculate attention weights, self-attention mechanisms use relationships between multiple variables in the same input sequence. As a result, DCNN is particularly helpful for tasks following feature extraction, as it can efficiently collect long-range dependencies and contextual information. To minimize spatial dimensions and reduce the sample size of feature maps, the DA-CNN can additionally include pooling layers. After feature extraction, the dilated CNN can be utilized for classification tasks such as distinguishing between benign and malignant lesions or identifying specific types of liver abnormalities. The extracted features serve as representations of the input images, which was the input to fully connected layers for tri-LC classification.

4 RESULTS AND DISCUSSION

In this section, the proposed DA-CNN efficiency was assessed using Matlab-2020b. The CT images as input are gathered from the accessible LiTS dataset. A detailed comparison and analysis is provided, focusing on the overall accuracy rate and the efficiency of the proposed LUNCERDEN model.

4.1 Efficacy scrutiny

The efficiency of the suggested DA-CNN was calculated based on standard performance metrics like precision (P), recall (R), F1 score (F1), accuracy (A), and specificity (S).

$$A = \frac{(TP+FP)}{(TP+TN+FN+FP)} \quad (11)$$

$$P = \frac{TP}{TP+FP} \quad (12)$$

$$S = \frac{TN}{TN+FP} \quad (13)$$

$$R = \frac{TP}{TP+FN} \quad (14)$$

$$F1\ = 2\left(\frac{P*R}{P+R}\right) \quad (15)$$

In these equations , TP and TN denotes true positives and true negatives of the images respectively and FP and FN specifies false positives and false negatives of the images. For the experimental setup, the tri classes of LC is defined as class-0 for NC, class-1 for HCC, and class-2 for CC respectively. The competence of the DA-CNN model for classifying several forms of LC is tabulated in table.1 and it is visually signified in figure 2.

Table 1. Efficacy evaluation of our DCNN model

Classes	A	S	P	R	F1
class-0	98.62	97.18	97.21	97.14	97.62
class-1	97.44	96.23	96.18	97.32	97.25
class-2	98.55	97.02	97.22	98.08	98.43

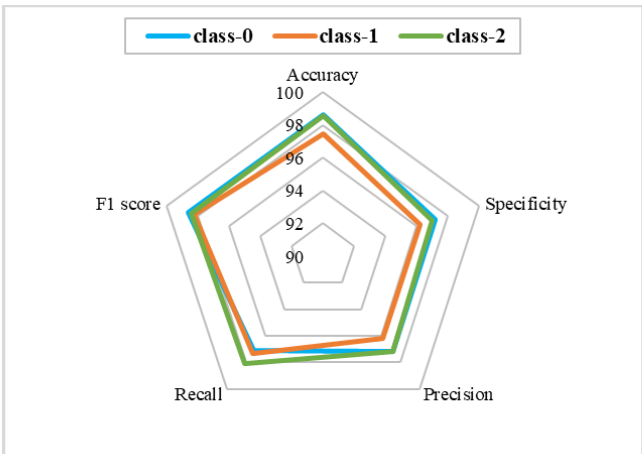

Figure 2. Classification performance analysis for tri-LC classes

The suggested LC-DCNN model classified the three different LC classes from the CT images as shown in figure 2. The suggested LC-DCNN is evaluated by metrics like recall, accuracy, precision, specificity, and F1-score. The suggested LC-DCNN achieves a total accuracy of 98.20% and shows an overall S of 96.81%, P of 96.87%, R of 97.51%, and an F1 of 97.76%.

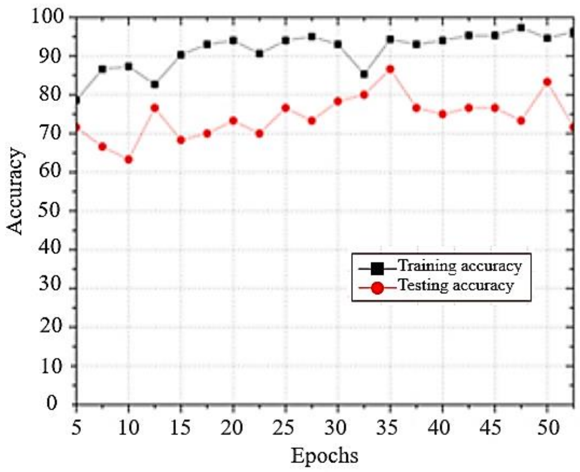

Figure 3. Accuracy graph of the proposed DA-CNN

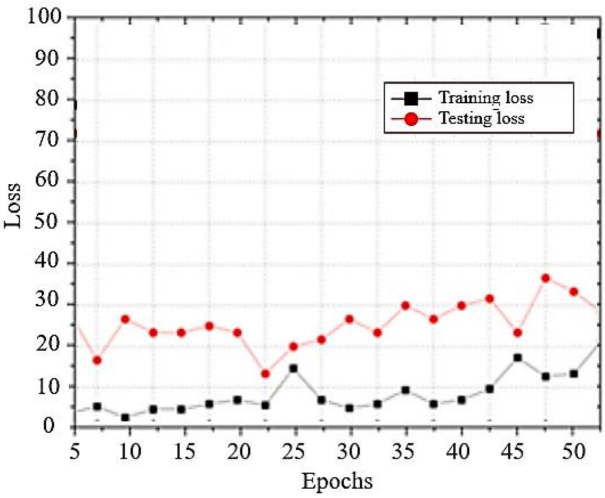

Figure 4. Loss graph of the proposed DA-CNN

Figure 3 presents the accuracy curve in which the accuracy range on the y axes against the number of epochs on the x axes. As epochs raises, the proposed DA-CNN demonstrates an improvement in accuracy. In Figure 4 , as the epochs and loss increase, the DA-CNN experiences a decrease in loss. Based on the gathered CT images, the proposed DA-CNN model proved to be effective in accurately classifying tri-LC cases. According to the findings, the DA-CNN achieves substantial performance in classification accuracy of 98.20%.

4.2 Comparative analysis

In this analysis, the competence of suggested and existing models was estimated using different metrics. The comparison assessment was competed among the proposed D-CNN with different classification techniques. The comparison of traditional classification networks is presented in table.2.

Table 2. Comparison of traditional models for classification

Models	Precision	Recall	F1 score	Specificity	Accuracy
ANN [22]	87.3	84.5	87.6	85.4	84.5
SNN [23]	88.5	87.2	86.4	90.2	92.5
DACNN	96.8	97.5	97.7	96.8	98.4

Table 2 presents a comparison of various conventional DL networks, identifying the best classification accuracy achieved. Though, despite their utilization, classic DL networks didn't yield superior outcomes in comparison to the suggested DCNN. The suggested DCNN shows an improvement in the total accuracy by 11.0%, and 9.87% than the ANN and SNN respectively.

Table 3. Accuracy assessment among Proposed and Existing models

Authors	**Methods**	**Accuracy**
Amin., et al., [15]	Optimized GAN	95.0%
Sakthisaravanan, B. and Meenakshi [18]	OPBS-SSHC	93.0%
Dong., et al., [19]	HFCNN	97.22%.
Proposed model	DA-CNN	98. 42%

Table 3 illustrates the assessment of the DA-CNN model with prior models based on LiTS dataset. The proposed DA-CNN model advances the total accuracy by 3.25%, 5.29%, and 0.99% than the Optimised GAN [15], OPBS-SSHC [18], HFCNN [19] respectively. The results shows that the proposed model outperforms the traditional models . So, the estimated fallouts of the proposed DA-CNN are extremely consistent for classifying the LC in its early stages based on CT images from LiTS datasets.

5. CONCLUSION

This paper presents an automated DL-based LC-DCNN for the identification of LC in its primary phases. The images are gathered from the publicly available LiTS database and these gathered images are pre-processed using Gaussian filter is used for reducing the noises and to smoothen the edges. The EM technique used for segmenting the liver region separately from the pre-processed CT images. Afterwards, DA-CNN was employed for identifying the LC into tri-classes. The efficiency of the suggested DA-CNN is measured utilizing the attributes like accuracy, sensitivity, precision, F1 score, and specificity values. The experimental fallouts disclose that the proposed DA-CNN attains an accuracy of 98.45%, that was comparatively better than the prior techniques. The proposed DCNN shows the significant improvement in the total accuracy by 11.0%, and 9.87% better than ANN and CNN respectively. Moreover, the proposed DA-CNN model advances the total accuracy by 3.25%, 5.29%, and 0.99% which is better than Optimised GAN, OPBS-SSHC, HFCNN respectively. Therefore, the outcomes obtained from the proposed DA-CNN are highly trustworthy for the early-stage classification of LC.

CONFLICTS OF INTEREST

The authors declare that there is no conflict of interest.

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AUTHORS

Ramakantha Reddy received an M.Tech. in computer science and engineering from JNTU, Anantapuramu in 2011 and Ph.D. from Vellore Institute of Technology, Vellore, Tamil Nadu, India in 2025. Currently, he is working as an Associate Professor in the Department of CSE(AI&ML) at Sri Venkateswara College of Engineering, Tirupathi. His current research includes data analytics, Machine learning, and IoT.

Prince Samuel is a dedicated researcher and academician with a strong foundation in Electronics, Embedded Systems, and advanced applications of Image Processing and Machine Learning. His academic journey began with a Bachelor of Engineering in Electronics and Instrumentation Engineering, Karunya University which laid the technical groundwork for his career. With a keen interest in embedded technologies and intelligent systems, he pursued a Master of Technology in Embedded Systems, Karunya University gaining specialized expertise in system design, hardware–software integration, and real-time applications. His academic pursuits culminated in a Ph.D. in Image Processing and Machine Learning, where he explored innovative methodologies for data-driven solutions, pattern recognition, and automation across multidisciplinary domains.

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