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ABSTRACT

More and more chromosomal and metabolic abnormalities are now known to cause cancer, which is typically fatal. Anybody component may become infected by tumor cells, which can be fatal. One of the most prevalent types of cancer is skin cancer, and its prevalence is rising around the globe. Early diagnosis and delineation of the lesion margins are crucial for precise malignant region identification and clinical treatment of skin lesions. Skin cancer incidence is greater than average, particularly melanoma, which is more dangerous because of its high rate of metastasis.

Therefore, early detection is essential for treating it before malignancy develops. The analysis and segmentation of lesion boundaries from dermoscopic images is done in order to solve this issue. A variety of techniques have been utilised, from textural assessment of the photographs to visual assessment of the images.

Keywords: skin cancer, convolutional neural network, deep learning, dermoscopic image, ISIC2018 dataset.

Classification: FOR CODE: 170203

Language: English

London Journals Press

LJP Copyright ID: 975827
Print ISSN: 2514-863X
Online ISSN: 2514-8648

London Journal of Research in Computer Science and Technology

Volume 22 | Issue 3 | Compilation 1.0

Dermoscopic Skin Cancer Image Segmentation and Classification using Machine Learning Technique

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ABSTRACT

More and more chromosomal and metabolic abnormalities are now known to cause cancer, which is typically fatal. Anybody component may become infected by tumor cells, which can be fatal. One of the most prevalent types of cancer is skin cancer, and its prevalence is rising around the globe. Early diagnosis and delineation of the lesion margins are crucial for precise malignant region identification and clinical treatment of skin lesions. Skin cancer incidence is greater than average, particularly melanoma, which is more dangerous because of its high rate of metastasis.

Therefore, early detection is essential for treating it before malignancy develops. The analysis and segmentation of lesion boundaries from dermoscopic images is done in order to solve this issue. A variety of techniques have been utilised, from textural assessment of the photographs to visual assessment of the images.

However, due to the sensitivity involved in surgical interventions or drug distribution, the accuracy of these techniques is poor for real clinical therapy. This offers a chance to create an automatic system that is accurate enough to be applied in a clinical environment. Epithelial tissue and basal cell carcinomas, as well as melanoma, which is medically severe and causes the majority of deaths, are the main subtypes of skin cancer.

Monitoring for skin cancer is therefore essential. Machine learning is one of the greatest ways to quickly and precisely identify skin cancer. To use the ISIC2018 database, the convolution neural network (CNN) deep learning technique was employed in this study to identify the two main categories of tumors, malignant and benign.

Skin lesions, comprising benign and malignant tumors, are included in this database. The images were initially enhanced and edited using ESRGAN. The pre- processing stage involved resizing, normalizing, and augmenting the images. Using a CNN approach, skin lesion images might be categorized based on an accumulation of data collected after numerous repetitions. The experimental results show that the proposed methodology performance is better than existing methodologies.

Keywords: skin cancer, convolutional neural network, deep learning, dermoscopic image, ISIC2018 dataset.

I. INTRODUCTION

Tumor is the unregulated growth of tissues in a particular body part. It appears that skin cancer is one of the global diseases that spreads the fastest.

Skin cancer is a condition in which uncontrolled development of abnormal skin cells occurs. Early identification and precise diagnosis are crucial for determining viable cancer therapy. The most common cause of skin cancer-related mortality in industrialized nations is melanoma, the deadly type of skin cancer. Squamous cell carcinoma, squamous cell, Merkel cell cancer, dermato-fibroma, microvascular, and benign pathology are the main kinds of melanoma [1].

Skin cancer is among the most lethal forms of cancer worldwide, and it is causing an increasing

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number of fatalities every day. It is also one of the cancer forms that spreads the fastest. However, if it is discovered in its early stages, therapy is doable [2]. Recent figures show that 20% of skin cancer cases progressed to the point where survival is impossible as a result of the illness.

Skin cancer is responsible for 50,000 deaths worldwide annually, or 0.7 of all cancer-related fatalities. Around USD 30 million is the anticipated cost of the procedure, which is prohibitive. Early skin cancer detection is essential to ensuring a benign course and lower mortality rates, however reliable cancer detection frequently relies on screening mammography with insufficient sensitivity, which is subsequently confirmed by clinical samples [3].

The use of this method for cancer detection and treatment response assessments is typically inappropriate. Artificial intelligence (AI) for diagnostic purposes is being used by a growing number of healthcare professionals to enhance and speed up the medical decision-making process [4]. However, the accurate analysis and adequate presentation of projected defects have been completely or mostly overlooked by presently offered AI research for clinical diagnosis, despite some recent signs of advancement in this arena. The scientific community has given computer-aided technology for the diagnostics interpretation of medical pictures a lot of attention [5]. These are effectively created and altered for the objectives of, among others, classifying and segmenting the area of interest (AOI), which in this case includes malignant spots. It goes without saying that early diagnosis and delineation of lesion borders are essential for the successful chemotherapy of cancer, particularly in the initial stages while the disease is still developing [6]. Each year, 9.6 million people die from cancer related causes and almost 17 million individuals are impacted by the disease. As a result, cancer is now the top cause of mortality globally. In the instance of skin cancer, it arises or develops in the epidermal cells and is one of the most common kinds of the illness in both children and adults. For the purpose of detecting cancer boundaries from dermoscopic pictures, many computer-aided methods have been created [7]. Due to its high probability of metastasis, carcinoma is not only the most common and lethal kind of skin cancer, it is also highly severe and destructive. The aggressive skin cancer known as melanoma arises from the uneven proliferation of melanocytes, which are colored skin cells. It can appear anywhere on the skin's epithelial tissue and is perhaps able to spread from the initial location of the malignancy to the chest and back. It has the highest fatality rate of any kind of skin cancer and its prevalence rate has increased by up to 4-6% yearly. Timely diagnosis is crucial since it raises the chance of survival for five years by up to 98%.

Given the information provided above on the prevalence and death rate of melanoma, early detection is even more important for those who are afflicted to receive appropriate care. There are two streams of techniques for the identification and fragmentation of lesion boundaries [8]: first, common methods that typically rely on the clinician's visual inspection; and second, semi-automated and done by machines methods that primarily use argument intensity values operations, pixel cluster - based techniques, level set strategies, deformable modeling techniques, deep-learning based techniques, etc.However, due to the inherent limits of the approaches and the shifting characteristics of dermoscopic pictures brought on by fluorescence emission and luminance in homogeneities, the majority of the techniques applied today are not moderately.

Because of this, more advanced techniques have become popular, like convolutional neural networks (CNNs). In this study, we aim to use CNN-based model topologies and attributes to the delimitation and segmentation of skin lesion boundaries. Additionally, we add our original innovation—image inpainting—to the already existing approaches that significantly improves segmentation results. Image inpainting is utilised to eliminate the hair complex working environment in the dermoscopic images that would otherwise hinder the design due to complexity in the images [9], along with other image preparation techniques including morphological procedures. In this study, the implementation of the suggested preprocessing approach is examined as well as the recommended technique's correctness. By using data from network accuracy, the Jaccard Index, the Dice score, and other performance standards that help us compare, we also compare our proposed technique to other ones that are currently in use [10].

II. LITERATURE REVIEW

This section outlines and lays out the pertinent research that has been done on the topic of segmenting skin lesions. The latest research that have used deep-learning techniques for the mentioned aim of lesion classification are given further prominence in this process. It is proposed that correct segmentation and delineation of skin lesion borders can benefit the physician at the first stages of diagnosis and detection as well as later on when classifying the lesion type.

Numerous research have been conducted in order to segment and characterize skin lesions. For a basic overview of these investigations, the reader is referred to the following two works by Oliveira et al. and Rafael et al. [11]. Following, we evaluate the literature in relation to two issues (i.e., pre-processing and segmentation techniques, respectively). Both elements fit into the larger technique discussed in this study since they have an impact on how the findings (the prediction) turn out. In order to blend out non- homogeneous parts, previous pre- processing methods must also be used since dermoscopic pictures have varied degrees of complexity and include different levels of textural, intensity, and feature inhomogeneity. The poor luminance and chaos in the photos make it difficult for investigators to segment skin conditions. The accuracy of fragmentation is impacted by these artifacts.

Celebi et al. [12] suggested a method that improves picture contrast by looking for ideal weights for transforming RGB photos into grayscale by maximizing Otsu's histogram bimodality metric. This method would produce superior results. While Beuren et al. [13] detailed the bilinear interpolation that may be performed to the picture for background subtraction, improvement led to a better adaptive capacity to discern between cancer and skin and enabled for precise resolution of the areas. The colored morphological filter highlights the lesion, and linearization is used to simply segment it. A technique to eliminate hair distortions from dermoscopic pictures was put out by Lee et al. [14].

To eliminate hair-like distortions from skin photographs, a morphological operations-based method was created. Hair, which is referred to as noise, can significantly affect segmentation outcomes when it is removed from skin pictures.

On noisy pictures, a median filter was shown to be useful. Images were smoothed using a nonlinear filter [15]. For efficient smoothing, Celebi et al., [16] states that the size of the filter to be employed must be proportionate to the size of the picture. Conventional machine learning techniques are used in the majority of picture segmentation jobs to extract features. Several key methods for precise segmentation are explained in the literature. An overview of a semi-supervised technique for separating skin lesions is given by Jaisakthi et al. [17]. For segmentation, grab-cut methods and K- means clustering are used. The latter adjusts the lesion's borders when the former divides the melanoma into smaller sections using graph cuts. Prior to feeding the input pictures to the pixel classifier, pre-processing methods including image normalization and noise reduction procedures are applied. Artificial bee colonies (ABC) were suggested by Mohanad Aljanabi et al. [18] as a technique for segmenting cutaneous lesions. The model is a swarm-based approach with fewer features that involves pre-processing of the digital pictures and finding the ideal melanoma threshold value via which the lesion is segregated using Otsu thresholding.

This method produces a high Jaccard Index and specificity. An approach for segmenting pictures using the Delaunay triangulation method was proposed by Pennisi et al. [19]. (DTM). The method uses two different pictures created by parallel classification methods, which are then combined to create the final lesion disguise. After removing artifacts from the pictures, one method removes the skin from the images to construct a segmentation mask of the lesion, while the second method makes use of Delaunay triangulation to create the mask. To acquire the identified lesion, these two are joined. The DTM approach is quicker than other techniques since it is computerized and does not need a training phase.

In their brief survey of border detection methods (such as edge-based, region-based, histogram thresholding, active contours and clustering, etc.), M Emre Celebi et al. [34] pay particular attention to assessment factors and processing concerns.

2.1 Materials and Methods

We used dermoscopic skin pictures from two publicly available datasets—PH2 and ISIC 2017—to train and test our classification algorithm. The latter was made available by the "International Skin Imaging Collaboration" (ISIC). Figure 1 displays illustrations taken from both databases.

In the Lesion Automatic segmentation, which is the first component of the 2017 ISBI Skin Lesion Analysis approaching Melanoma Specific diagnostic, we compared our model. We compared our performance of the model with cutting-edge pipelines using the ISIC-17 test set, which consisted of 600 photos.

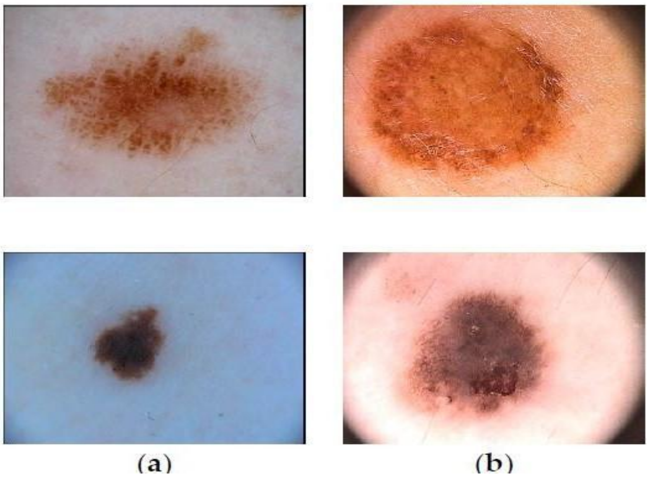

Figure 1: Examples of the ISIC-17 Dataset (A) and PH2 Dataset (B)

Additionally, the PH2 dataset, which contains 200 dermoscopic pictures, comprising 40 melanoma, 80 normal nevi, and 80 atypical nevi images, was used to evaluate our model. We describe our developed approach and the outcomes that followed after it was trained and evaluated on the datasets (details will be provided later). It is important to note right away that we presented an approach, also known as the intersecting over unity overlapping that outperforms other comparable methods, both in terms of model correctness and in pixel-by-pixel clustering algorithm (sometimes also referred to as the Jaccard Index). We now go on to detail each portion of the suggested technique, point by point. Before being used as input by the CNN model, images are first processed using procedures including resizing, scaling, hair removal, and data centered. Morphological techniques are used to remove noise. We used the following pre-processing techniques, and we saw encouraging results. Prior to feeding photographs into the neural network, it is a good idea to resize the images. It enables the model to convolve more quickly, reducing computing time and addressing memory limitations. Dermoscopic pictures arrive in different sizes, therefore to account for these individual variations, the images and the ground truths they correspond to are down sampled to 256 256 resolution. The labels for each RBG picture are in the PNG file format, whereas all of the RGB images are in the JPEG file format.

Image normalization and standardization: To eliminate concerns with weak contrast, images are normalized prior to training. By rescaling the picture between 0 and 1, or normalizing the image's pixel values, the input data is centered on zero in all dimensions. The picture is normalized by deducting it from its mean value, which is then multiplied by the image's standard deviation.

III. MODEL ARCHITECTURE

Visual identification and object detection issues are now being solved using deep learning systems. For feature extraction, CNN models have demonstrated superior performance than semi-automated techniques. The encoder-decoder-based U-Net architecture has produced noteworthy outcomes in the segmentation of medical images. These networks provide binary classification models as their output. CNN models often consist of a mix of layers (i.e., convolutional, max pooling, batch normalization, and activation layer). The usage of Deep learning architectures in computer aided medical diagnosis is common.

A Convolution layer was developed for this purpose using the ISIC 2017 dataset. Both U-Net and ResNet are used as inspiration for the network design (as illustrated in Figure 3). The U-Net pipeline serves as the foundation for the expanding path (deconvolutional side), while the ResNet framework serves as the foundation for the training part (convolutional side). The network has 50 layers overall and operates in an encoder-decoder mode (ResNet-50). Enter 256 x 256 resolution pictures.

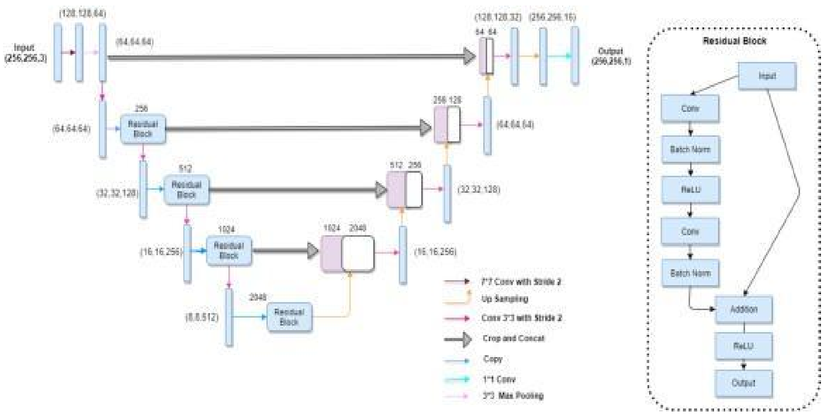

Figure 2: Schematic Diagram Representing UResNet-50. the ResNet-50 Encoder Is Displayed on the Left, While the U-Net Decoding Is Displayed on the Right. the Channel Widths of the Receiving Extracted Features to Each Square Are Provided in the Parentheses

On the expanding side, a max pooling layer with a kernel of 3 x 3 and a stride of 2 that divides the input width in half is constructed after the initial convolutional layer. 3 convolutional layers per repeating block are inserted; the 1 x 1 convolution layer is designated before and after each 3 x 3 convolution operation. Prior to the 3 x 3 convolutional layer, the amount of input channels is decreased, and once more, the 1 x 1 is established to restore proportions. This so-called "bottleneck" design shortens the network's training period. We trained our model for 100 iterations and used data augmentation during runtime, which improves performance since additional data increases the reliability of the algorithm so that it can categorize more accurately, having a major impact on the classification outcomes. We tripled the dataset by rotating the photos in 3 components. In the event that the model damage does not reduce after 10 epochs, early ending is established, and the learning rate is decreased. Our model came to an end after about 70 epochs. Employing pre-trained weights acquired during training on the ImageNet dataset, deep learning was used to train the model on our set of data.

IV. RESULTS AND DISCUSSION

The International Skin Imaging Collaboration ISIC 2017 provided the pictures used to assess our model. The ISIC 2017 training set, which included 2000 photos of skin lesions, served as the basis for our CNN model's training. This procedure resulted in a 70-epoch overall training accuracy of 0.995. Figure 3 highlights how the training group's accuracy varied from the validation group's during training.

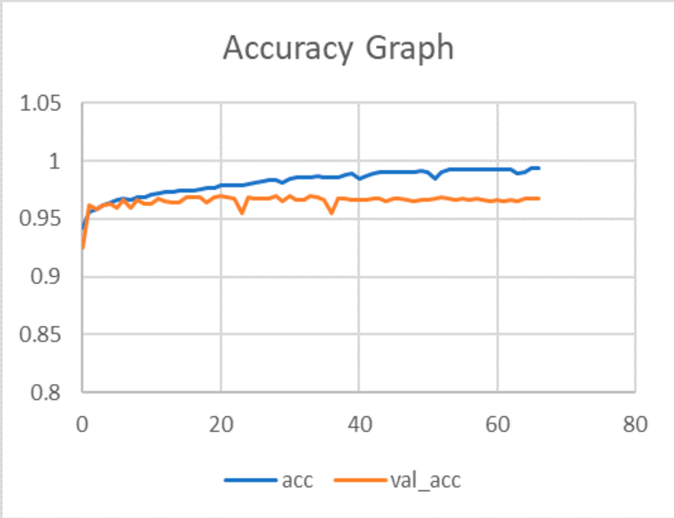

Figure 3: Training and Validation Accuracy of the Proposed Convolutional Neural Network Model for 70 Epochs

The validation and test set from the ISIC 2017 dataset were used to test the model. Additionally, the model was assessed using the PH2 dataset, which consists of 200 dermoscopic pictures. The effectiveness of the suggested CNN model could also be evaluated using the ground facts that were also accessible. Before being input into the CNN architecture as shown in Figure 3, all pictures underwent pre-processing. Accuracy of the suggested convolutional model of neural networks for 70 iterations during training and validation. Convolutional layer characteristics were specified during the training phase. The model parameters were left alone throughout the assessment procedure in order to gauge how well our model performed given the initial values.

Figure 4 displays the outcomes of several patients. To assess the effectiveness of binary classifiers, the receiver operating characteristics (ROC) curve was utilized. A plot of the true positive rate (Sensitivity) against the false positive rate (Specificity) at various thresholds is known as a ROC. In this study, the lesion area is segmented, with 1 denoting the lesion region and 0 denoting the black portion of the picture. The ROC curve is the best evaluation method for determining class separability. A curve's individual data points each display values at a certain threshold.

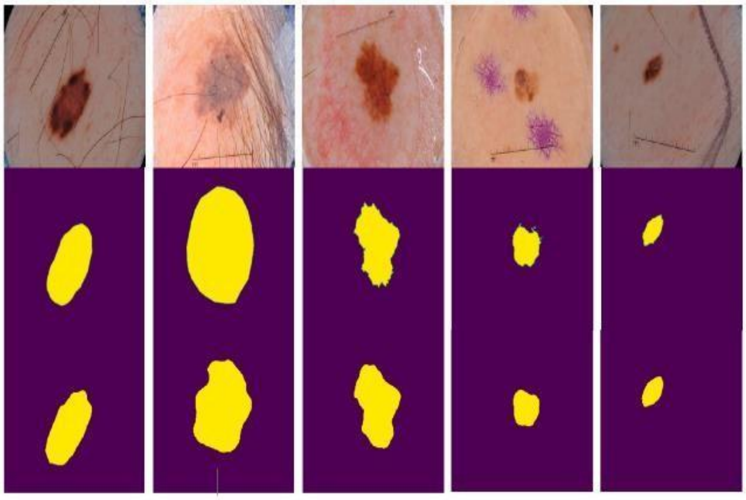

Figure 4: Example Results of Various Images

To determine the effectiveness of the hair removal method, the model was evaluated on the ISIC-17 dataset both with and without pre-processing.

When the inpainting approach was not used to remove the hair structures from the pictures, a Jaccard of 0.763 (as shown in Table 4) was obtained. This value increased significantly to 0.772 with the use of the pre-processing technique. The goal was to more accurately segregate the lesion locations using this study than with previous techniques. Our network was tested against three different sets of images: the PH2 dataset, the ISIC 2017 test group, and the ISIC 2017 validation group. There were 150 dermoscopic pictures in the validation group and 600 in the test group. The PH2 dataset, which is a well-known dataset, was employed to further assess our network and compare the findings to those of other competing methods and challenge members.

V. CONCLUSION

In order to create a computer assisted diagnosis system for skin cancer, skin lesion segmentation is a crucial step. In this study, we successfully created a CNN-based skin lesion segmentation algorithm that deleted hair structures from the dermoscopic pictures, greatly increasing accuracy. The Jaccard indices we got from the ISIC-2017 dataset and the PH2 dataset, on which we evaluated our model architecture, were 0.772 and 0.854, respectively. When compared to cutting-edge methods in terms of the Jaccard index, our suggested strategy produced encouraging results. Additionally, our CNN model outperformed the existing approaches in the literature when evaluated on the PH2 dataset and the ISIC-17 test set. It also yielded superior segmentation. According to empirical findings, the U-Net and ResNet combo produces excellent outcomes. To minimize the model from imbalanced datasets, the small amount of training data utilized must be heavily supplemented. Therefore, a huge dataset is required for the model to be more accurate and broader. Additionally, the model was designed to be complicated and effective in order to produce state-of-the-art outcomes, which requires more time to train than the traditional U-Net. In order to alleviate overfitting issues, we will be employing a larger dataset in the future. We will also be hyper- tuning the model parameters. The developed model can also be improved using a conditional random field (CRF) approach.

Author Biography

Dr. E. Kesavulu Reddy working as a Senior Assistant Professor in the Department of Computer Science College of Commerce Management & Computer Science S.V.University, Tirupati, Andhra Pradesh, India-517502. He received Doctor Philosophy in Computer Science in the area of Elliptic Curve Cryptography from S.V.University ,Tirupati. He was elected as an Executive Member in S. V .U Teacher Association from 2014 to 2016. Also, he was elected as

Vice-President Unanimously elected in S.V.U Teachers Association from 2016 to 2018.

He was appointed as a NSS Programme Officer on 07-09- 2017 in the NSS Unit of S.V.University College of Commerce Management & Computer Science, Tirupati. He organized NSS Special Campaign Programs, Regular NSS Campaign Programs and Mega Blood Donation Camps at Thummalagunta, Upperapalli SC & ST colonies of Thummalagunta & Upperapalli , NSS Unit and NSS Bhavan, S. V. University, Tirupati from 2017 to 2022. He was organized two National Conferences i.e. "National Conference on Information Security & Internet of Things (ISIoT-2K19) 20-21, December 2019, and National Conference on Information Security & Data Security in Cloud Computing (ISDSCC2K21) 29-30 April 2021". Two PhD 's was awarded under his Supervision during the period from 2014 to 2020. He had published 71 papers in various UGC reputed International Journals one in National Journals. He had attended and presented 52 papers in National conferences 16 papers presented and published in various International Journals. He published 09 books i.e., one in Book Publishers International United Kingdom and 08 books are published with ISBN Number.

He received Dr. Surveypalli. Radhakrishna Life – Time Achievement National Award with Gold Medal, Memento and Certificate from IRDP Group of Journals, Chennai on 30th May 2018.

He was honored with "Fellow of Computer Science Research Council (FCSRC)" from Open Association of Research Society from Global Journals, U.S.A) on 31st January 2019 for the performance of published research work in the world. He was awarded with "Best Outstanding Researcher 2020" International Award and Best Outstanding Scientists 2020 with Gold Medal, Memento and Certificate from Kamarajar Institute of Higher Education Theme, Madurai-Tamil Nadu. Also, he received "Best Outstanding Scientists 2021" International award from International Scientists on Science, Engineering & Medicine 2021, VDGOODTM TECHNOLOGY FACTORY, Coimbatore-Tamilnadu.

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