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Semantic segmentation of palpebral conjunctiva using predefined deep neural architectures for anemia detection

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Abstract

Non-invasive detection of anemia is generally done by physical examination of regions like palpebral conjunctiva, fingernails, tongue and palmar creases. However, such examination is subject to large inter- and intra-observer bias. This problem can be alleviated by automating the anemia detection process through computerized analysis of images of these regions. The automated process includes sub-processes like preprocessing, segmentation of region-of-interest (ROI), ROI analysis or feature extraction, and classification. Of all these sub-processes, segmentation is the most crucial one as it helps in the precise extraction of ROI where the most crucial information for decision making lies. Recently, deep learning-based architectures have given exemplary performance in biomedical image segmentation. This paper is unique in a sense that it simulatneously analyzes performance of five deep learning-based architectures namely UNet, UNet++, FCN, PSPNet, and LinkNet. The experiments are performed on customly built dataset comprising of 2592 palpebral images of the pediatric population. The experimental results indicate that as compared to its counterparts, the LinkNet architecture performs the best. Its scores 94.17%, 90.14% and 93.78% for the accuracy, intersection-over-union (IoU), Dice score performance metrics, respectively. The study concludes that LinkNet architecture can be used for real-time segmentation of palpebral conjunctiva from images.

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Keywords: Medical Imaging, Image Segmentation, Deep Learning, Image Processing, Anemia Detection, Haemoglobin, Palpebral Conjunctiva

1. Introduction

Haemoglobin, *abbreviated as Hgb or Hb*, is an iron-containing protein in the red blood cells that carries oxygen from the lungs to other body parts. In a healthy adult, the *Hb* level in the blood varies from 12 to 16 g/dl for females and 14 to 18 g/dl for males [1]. However, *Hb* levels may drop considerably due to various medical ailments, nutritional inadequacy, and bone marrow abnormalities. This leads to a serious hematological disorder known as *anaemia*, resulting in body weakness, reduced cognitive ability, emotional instability, paleness of skin and even cardiac arrest

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in worst cases [2]. Anaemia has been marked as a serious health issue by the World Health Organization (WHO) amongst young children and pregnant women[1].

The most common way to monitor *Hb* levels and detect anemia is through invasive blood tests. The invasive blood tests are painful and carry the risk of hospital-acquired infection. Thus, it is preferred to detect anemia in a non-invasive way through visual examination of body parts such as nail beds, tongue, palmar crease and palpebral conjunctiva [3, 4, 5]. However, such an examination is to be done by a highly skilled medical expert who can correlate the visual cues with the presence of anaemia. Moreover, the manual examination is prone to human error, inter- and intra-observer bias and generates non-reproducible results [6]. Thus, there is a severe need to automate the anemia screening process using machine-aided tools.

Recently, many computerised systems have been developed to detect anaemia in a non-invasive or minimally invasive manner. Majority of such methods are based on spectrophotometry, which uses Beer-Lambert law, i.e, $I_o = I_i.e^{-\alpha.C.D}$ where I_i refers to intensity of incident light, α is the light absorption coefficient, C is concentration of *Hb* and D is depth of path to determine *Hb* levels. Commercially available systems such as Pronto-7® [7] and Haemospect® [8] are based on the same principle and are widely used to make clinical decisions. However, the sensitivity results of such non-invasive devices is still not at par with the results of the invasive methods [9]. This calls for improvement in the technology to measure the level of *Hb* in a non-invasive manner.

Recent advancements in deep learning have provided efficient solutions for the problems across the biomedical domain [10, 11, 12]. They can also be used to develop sophisticated computer-aided diagnosis (CADx) systems for anaemia detection using images of body parts such as conjunctiva, and fingernails. Such systems would exactly quantify the parameters such as pallor and erythema index (EI) from images. The CADx system for anemia detection generally consists of the following sub-processes: preprocessing, segmentation, feature extraction and classification.

In this paper, we have specifically focused on the segmentation part as the performance of the later sub-processes, i.e, feature extraction and classification, are highly dependent on it. The major contribution of this paper is as follows:

1. A customised dataset of palpebral conjunctiva has been collected using smart phone based mobile application and has been labelled by the experts to perform segmentation.

2. The comparatative analysis and evaluation of the five predefined deep architectures namely UNet, UNet++, FCN, PSPNet and LinkNet for segmenting palpebral conjunctiva has been performed using the evaluation metrics such as accuracy, IoU and dice score.

3. The results of the evaluation indicates that LinkNet architecture is better suited for palpebral conjunctiva segmentation as compared to its counter parts.

4. This result can be used by the researchers working in the field to develop state-of-the-art non-invasive image-processing based anemia detection system.

The rest of this paper is organised as follows. Section 2 provides a succinct review of literature enumerating the recently presented segmentation approaches with the application for anemia detection. The details of the dataset used for experimentation and network architectures used for segmentation are presented in Section 3. Section 4 presents the experimental results. Finally, conclusions are detailed in Section 5.

2. Literature Survey

During the past few years, researchers have focused on the development of non-invasive automated and semi-automated methods to detect anemia from conjunctiva images. The underlying hypothesis for such research is the strong correlation between haemoglobin values and color of palpebral conjunctiva [13]. Prakhar et al. [14] proposed a semi-automated approach to detect anemia from the images of eye conjunctiva. In their work, they used a dataset consisting of 99 images, which is augmented using operations like mirroring, rotation and translation. Due to the irregular shape of the conjunctiva, they performed manual segmentation to extract the region-of-interest (RoI). Later,

[1] https://www.who.int/health-topics/anaemia

feature extraction and classification are performed to detect anemia. A similar manual extraction of conjunctiva portion has also been performed in [15] and [16].

Some research works such as [17, 18] have used primitive image processing-based techniques such as thresholding to extract conjunctiva. Prakash et al. [17] empirically determined a threshold value of 210 and applied it to the red component of the image to generate a binary mask of the conjunctiva. Similarly, Sedki [18] used a threshold value of 225 on the red channel followed by median filtering. The largest segment in the image is then extracted as conjunctiva. Bhasker et al. [19] extracted eye conjunctiva by using triangle algorithm, a type of thresholding algorithm, and segregated palpebral conjunctiva from the background. The extracted ROI is then converted from RGB to L*a*b color space and a* component is used in the post-processing operations to refine the extracted ROI. Vitoantanio et al. [20] also performed RGB to L*a*b color space conversion prior to image thresholding for segmentation. The a* values of the image are extracted, fine-tuned using Gaussian filter and morphological operations, and then used for segmentation. Dimauro et al. [21] also used a combination of a* component, Otsu thresholding algorithm, morphological operations and contour detection to segment conjunctiva from an image.

A different approach is adopted in [22], which used Haar wavelet-based Viola-Jones algorithm [23], for the initial phase of eye segmentation from the entire face. It is later followed by histogram equalization and binary thresholding on the red channel.

The image processing-based approaches are fragile and their performance highly depends upon the condition in which the image is acquired. The machine learning-based approaches on the other hand are robust and less susceptible to image acquisition issues. Recent advances in deep learning have given exemplary solutions for problems in varied domains such as computer vision, medical image analysis, and natural language processing. In the image processing domain, convolutional neural networks (CNNs) have given good results due to their inherent abilities to process the spatial context. Although CNNs have shown remarkable performance in the field of medical image segmentation, a limited amount of research has been done on conjunctiva segmentation. In [24], Saldivar et al. used 7-layer CNN to segment conjunctiva from eye images captured using a smartphone. Transfer learning-based semantic segmentation of conjunctiva using UNet [25] has been performed in [26]. Benchmark performance of 85.7% as intersection-over-union (IoU) score is attained by fine-tuning the original UNet architecture for segmentation of conjunctiva region in [26]. Notable papers from the literature review that have given good results are summarised in Table 1.

3. Materials and Methods

This section provides details about the dataset and network architectures used in this study. The section is further organized into five sub-sections: dataset, experimental setup, neural architectures used for segmentation, and performance metrics.

3.1. Dataset

The dataset contains eye images of anemic and non-anemic pediatric patients, acquired at a tertiary healthcare centre in North India from 11-March-2022 to 15-May-2022 using a mobile application running on a smartphone. The smartphone has four primary cameras with a resolution of 64MP, 8MP, 2MP, and 2MP. The color RGB images are captured from a distance of 2 inches - 5 inches from the patient using auto-focus mode and are stored in .png format.

The conjunctiva images of both eyes of 162 subjects have been captured after obtaining informed consent from the parent/guardian of the subject. Thus, a total of 324 images are captured. Data augmentation using operations such as mirroring, horizontal and vertical flips are performed to increase the number of sample images to 2592.

For training, testing and validation of neural architectures, ground truth masks for conjunctiva are manually created for each sample image using the computer vision annotation tool (CVAT)[2]. The CVAT tool generates polygon masks based on the number of points drawn around the ROI. The dataset consisting of acquired images and the associated masks is available for research purposes upon request[3].

[2] https://cvat.org/
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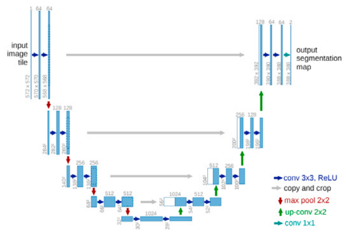
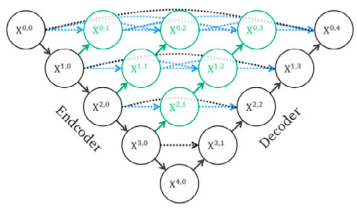
Reference	Algorithm	Dataset	Performance Metrics		
			Dice Score	Accuracy	IoU
Delgado-Rivera et al. (2018) [22]	Viola-Jones algorithm [23] and binary thresholding	Custom dataset Total images (115)	N.A	0.922	N.A
Dimauro and Simone (2020) [27]	Normalised cuts approach	Custom dataset (94 patients)	0.736	0.937	N.A
Kasiviswanathan et al. (2020) [26]	U-Net based conjunctiva segmentation model (UNBCSM)	Custom dataset 135 original images 500 images generated	N.A	N.A	0.857

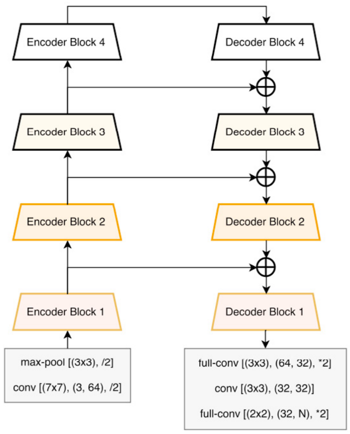
Table 1. State-of-the-art algorithms for palpebral conjunctiva segmentation

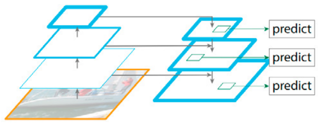


(a) UNet [25]

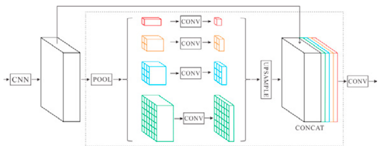


(b) UNet++ [30]





(c) FPN [31]



(d) PSPNet [32]

(e) LinkNet [33]

Fig. 1. Various network architectures used in the study to perform conjunctiva segmentation

3.2. Experimental Setup

All the models selected for the study have been trained and tested under the same conditions. All the possible hyperparameters such as learning rate, batch size and loss functions have been kept the same to draw a fair comparison between them. Moreover, Bayesian optimisation has been used to finetune the final values of all the hyperparameters. The learning rate of $1e-3$ has been used to train the model and avoid explosion or vanishing gradient problems. Adam optimiser [28] in combination with cosine annealing scheduler has been used with the weight decay of $1e-5$. A fixed batch of 4 images is passed to every epoch and the training process is iterated for 200 epochs. Besides, all the models have been pre-trained on ImageNet dataset [29]. The use of pretrained networks speedup the training process. The entire dataset has been split into a ratio of 80:20 for the training and validation respectively. The train set has further been split into 80:20 to utilise the latter images for validation results after every iteration. All the experiments have been performed on the same hardware, i.e. a machine with Nvidia GeForce RTX 2080Ti Graphics Processing Unit (GPU), 2.30 GHz Intel(R) Xeon(R) Gold 5218 Central Processing Unit (CPU) and 128 GB RAM. An open source Python framework, PyTorch along with segmentation models[4] library, has been used in this study.

[4] https://smp.readthedocs.io/en/latest/models.html

3.3. Predefined Architectures used for Conjunctiva Segmentation

In this work, five popularly used segmentation models namely, UNet, UNet++, FPN, PSPNet and LinkNet have been described and used to perform conjunctiva segmentation. The architectures of the used models are depicted in Figure 1. The backbone network chosen in this study is DenseNet-121 [34] which serves as a feature extractor to each of the networks. The following is a brief description of the used networks:

1. **UNet:** This architecture is proposed by Ronneberger et al. [25] in 2015 specifically for biomedical image segmentation. The model consists of two paths: encoder (contracting) and decoder (expansive). The expanding path is geometrically symmetrical to the contracting path, resulting in a network that resembles the letter 'U' in English. The encoder helps to down-sample the image using a pre-trained convolutional network whereas the decoder helps to upsample the resultant features using transposed convolutions. Additionally, the concatenation operation is performed between the corresponding feature maps of the encoder and decoder at the same level. At the last stage, 1×1 convolution is used to map multiple feature maps to the desired number of output classes.

2. **UNet++:** It is an improved and efficient version of the original UNet architecture [35]. It optimises the results by adding dense nested skip connections between each upsampling block. Each node in a decoder receives not only the final aggregated feature maps but also the intermediate aggregated feature maps and the encoder's original samescale feature maps, due to dense connectivity. This results in the extraction of multiscale feature maps from convolutional paths and thus is considered more superior network than simple UNet.

3. **Feature Pyramid Network (FPN):** FPN gained attention in the field of semantic segmentation because of its property to exploit multiscale hierarchy in a pyramid manner and thus improve scale invariance [31]. To induce both low- and high-level features, top-down and the bottom-up pathways have been designed. The bottom-up network is a basic convolutional network (DenseNet-121 in our case) which downsamples the feature maps. The final stage of the bottom-up path is used as a set of features to design the corresponding top-down pathway. The top-down architecture first upsamples (by a factor of 4) the feature maps obtained from the previous network and then enhance the semantic accuracy using lateral connections from the bottom-up pathway at the same level. It is proceeded by a 1×1 convolutional layer to reduce the dimensions of the channel and later merged using element-wise addition. Finally, a 3×3 convolution is also used to reduce the anti-aliasing effect of all the upsampling operations and a mask image is obtained. Thus, the goal of this network is to leverage the pyramidal hierarchy of the feature maps by combining semantically weak and strong features without any additional costs.

4. **Pyramid Scene Parsing Network (PSPNet):** PSPNet is one of the popularly used segmentation networks that infuses the advantages of the pyramid pooling module in the network [32]. Feature maps obtained from the encoder are pooled at various scales (6, 3, 2, 1) which are later convolved using 1×1 to reduce the number of channels at each layer. The pyramids of small size capture low-level features and those with large sizes take into account high-resolution features. Then, all the convolved features are upsampled by a factor of 8 to preserve input-output spatial dimensions. All the feature maps obtained from upsampling are later concatenated with the original feature map and are followed by a convolution layer to generate an output prediction map.

5. **LinkNet:** Architecture of the LinkNet model is based on encoder-decoder structure and has a similar structure as that of UNet [33]. It encourages the use of residual connections in the encoder which has been taken care of by the DenseNet model. Secondly, it replaces the process of feature stacking with feature addition to enhance the quality of final feature maps. Thus, it is expected to produce fine quality output masks as compared to that generated by UNet.

3.4. Evaluation Metrics

Accuracy of all the segmentation models is evaluated in terms of true positives (TP), true negatives (TN), false positives (FP) and false negatives (FN) using the following three performance metrics.

1. **Accuracy**: It denoted the number of pixels that have been segmented accurately to the total number of pixels in an image. It is calculated as $Accuracy = \dfrac{TP + TN}{TP + TN + FN + FP}$.

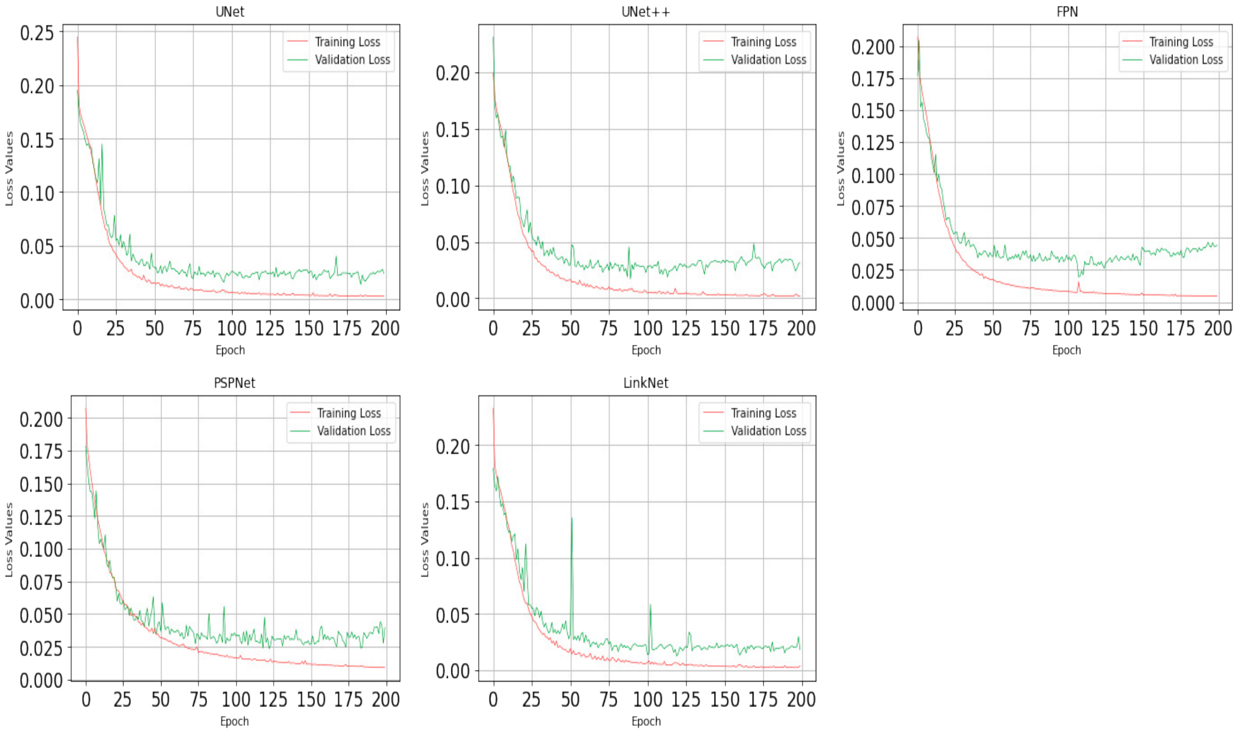


Fig. 2. Training and validation loss for various models

2. **Intersection over Union (or Jaccard Index)**: It is the most popularly used metric to evaluate the performance of any segmentation model. It measures the degree of the overlapped region between predicted and actual segmentation areas. It is calculated as $IoU = \dfrac{TP}{TP + FN + FP}$.

3. **Dice Score (or F1 Score)**: This metric also measures similarity between the ground truth and model predictions. IoU and Dice Score are positively correlated, i.e, if IoU measures higher similarity, Dice Score will predict the same. It is calculated as $Dice\ Score = \dfrac{2TP}{2TP + FN + FP}$.

4. Results

The quantitative results of conjunctiva segmentation for the five models under consideration are listed in Table 2. The loss convergence graphs during training and validation for every model are depicted in Figure 2. Experimental results indicate that three networks namely UNet, UNet++ and LinkNet are the top-performing models that excelled in the segmentation task. In addition to accuracy, we also considered space occupancy and training time factors to compare the models. *Space occupancy* refers to the disk space used to store the parameters of the model. *Training time* is directly related to the cost of the model development. The results of the top three models are narrowed down to choose the best model for semantic segmentation. It is observed that UNet++ has the highest number of parameters associated with it and took longer to train. After comparing all the metrics of UNet and LinkNet, it is concluded that LinkNet is the most suited model for conjunctiva segmentation. Qualitatively, the performance of models can be verified by looking at the segmentation results presented in Figure 3. The performance of LinkNet is also compared with the state-of-art models proposed for conjunctiva segmentation. The model proposed by Dimauro and Simone (2020) [27] for conjunctiva segmentation attained Dice score and accuracy of 73.6% and 93.7%, respectively. The network by Kasiviswanathan et al. [26] attained IoU score of 85.7%. In the performed experiments, LinkNet attained

Fig. 3. Qualitative analysis of state-of-art comparison with proposed model

Dice score of 93.78%, accuracy of 94.17%, and IoU score of 90.14%. The comparison of performance scores of LinkNet and other state-of-the-art models is given in Table 3.

5. Conclusion

In this paper, five pretrained segmentation architectures that are finetuned on a customised dataset are used for conjunctiva segmentation. To find the most suitable model, five state-of-art models namely- UNet, UNet++, FCN, PSPNet, and LinkNet are compared, keeping DenseNet-121 as the backbone of the encoder part. Experiments are performed to analyse the effectiveness of these models to segment palpebral conjunctiva from eye images. The models are ranked based on accuracy, training time and space occupancy. Additionally, the considered network architectures are compared with other state-of-the-art models specifically proposed for conjunctiva segmentation. The results of evaluation indicate that LinkNet has accuracy of 94.17%, IoU of 90.14%, Dice Score of 93.87%, which is better as compared to its counterparts. It is also better as compared to state-of-the-art methods by genuine margin. Our experiments suggest that the LinkNet model is better suited for palpebral conjunctiva segmentation as compared to its counterparts. The work carried out in this paper can be extended to extract features from the segmented region and perform anemia detection.

Model	Code Repository	Total Parameters (TP), Size in MB (S) and Time per epoch in sec (TT)	Performance Metrics (%)	Highlights
UNet [25]	https://github.com/milesial/Pytorch-UNet	**TP:** 12.9M, **S:** 204.27, **TT:** 209.41	**Acc:** 94.12, **IoU:** 90.05, **Dice:** 93.76	• Allows usage of context and location at global level • Works well with less training data too
UNet++ [35]	https://github.com/MrGiovanni/UNetPlusPlus	**TP:** 29.2M, **S:** 267.08, **TT:** 529.98	**Acc:** 94.15, **IoU:** 90.12, **Dice:** 93.79	• Focuses on fine details of features • Robust to selection of network depth
FPN [31]	https://github.com/jwyang/fpn.pytorch	**TP:** 8.6M, **S:** 228.46, **TT:** 187.02	**Acc:** 93.34, **IoU:** 89.95, **Dice:** 92.34	• Exploits multi-scale features • High-detection precision
PSPNet [32]	https://github.com/hszhao/semseg/blob/master/model/pspnet.py	**TP:** 1.7M, **S:** 177.88, **TT:** 149.47	**Acc:** 91.85, **IoU:** 87.52, **Dice:** 92.31	• Increase in receptive field without significant increase in parameters • Pays attention to local and global information
LinkNet [33]	https://github.com/e-lab/pytorch-linknet	**TP:** 9.7M, **S:** 192.14, **TT:** 201.83	**Acc:** 94.17, **IoU:** 90.14, **Dice:** 93.87	• Encourages use of skip connection to prevent gradient problems • Adds the feature maps at every level in network

Table 2. Performance comparison of various models

Reference	Models	Dataset	Performance metrics		
			Dice	Accuracy	IoU
Delgado-Rivera et al. [22]	Viola-Jones algorithm [23] and binary thresholding	Custom (115)	N.A	92.2	N.A
Dimauro and Simone [27]	Normalised cuts approach	Custom (92)	73.6	93.7	N.A
Kasiviswanathan et al. [26]	U-Net based conjunctiva segmentation model (UNBCSM)	Custom (608)	N.A	N.A	85.7
Abhishek Chaurasia et al. [33]	LinkNet	Custom (2592)	**93.78**	**94.17**	**90.14**

Table 3. Comparison between LinkNet and state-of-the-art models used for conjunctiva segmentation

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- **Conflict of Interest:** The authors declare that they have no conflict of interest in this work.
- **Data Deposition:** In this work, the authors have collected and used custom dataset for performing the experiments.

[5] https://dst.gov.in/

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