

Generating captions in English and Marathi language for describing health of cotton plant

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ABSTRACT

Humans' basic needs include food, shelter, and clothing. Cotton is the foundation of the textile industry. It is also one of the most profitable non-food crops for farmers around the world. Different diseases have a significant impact on cotton yield. Cotton plant leaves are adversely affected by aphids, army worms, bacterial blight, powdery mildew, and target spots. This paper proposes an encoder decoder model for generating captions in English and Marathi language to describe health of cotton plant from aerial images. The cotton disease captions dataset (CDCD) was developed to assess the effectiveness of the proposed approach. Experiments were conducted using various convolutional neural network (CNN) models, such as VGG-19, InceptionResNetV2, and EfficientNetV2L. The quality of generated caption is evaluated on BiLingual evaluation understudy (BLEU) metrics and using subjective criteria. The results obtained for captions generated in English and Marathi language are comparable. The network combination of EfficientNetV2L and long short-term memory (LSTM) has outperformed the other combinations.

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1. INTRODUCTION

The immediate basic needs of human includes food to eat, shelter for safety and clothes to cover body. As cotton is natural fibre, it is backbone of textile industry. The cotton is also one of the profitable non-food crop for farmers worldwide. The Figure 1 shows the world production of cotton from 2016 to 2020 [1]. The Figure 2 shows top 10 cotton producing countries during 2016 to 2021 [1]. During this period India was largest cotton producer. The Maharashtra, Gujarat, and Telangana are top cotton producing states from India [2]. Marathi is official language of Maharashtra State and is third largely spoken language in India [3].

The cotton crop experiences heavy yield loss due to different diseases [4]. The diseases also affect the quality of fiber made from cotton [5]. The leaves of the cotton plant are affected due to aphids, army worm, bacterial blight, powdery mildew, and target spots. It is difficult to physically verify health of each plant and identify the type of disease if plant is affected due to it. This paper proposes encoder decoder approach to describe the health of the cotton plant using captions in English and Marathi language. The aerial images of the farmland taken using drone or unmanned aerial vehicle are used for caption generation. The methods used for caption generation can be divided into three categories: encoder-decoder approaches [6]–[11], object

recognition approaches [12], and image retrieval approaches [13]. When compared to other methods, the encoder-decoder strategy has provided better results [14]. Previously, researchers focused solely on identifying cotton plant illnesses from leaf image [4], [5], [15]–[17] and did not contemplate using captions to describe the plant's health from aerial images.

This paper proposes encoder-decoder model to not only describes the health of cotton plant using a caption but also to explicitly specify the disease due to which the plant is affected. Moreover, the captions are generated in English as well as in Marathi language which is native language of farmers in Maharashtra State of India where cotton is largely produced. Five commonly affecting diseases namely aphids, army worm, bacterial blight, powdery mildew, and target spots are considered for experimentation. The dataset is also developed to verify the performance of the model.

The rest of the content of the paper is organized as follows: section 2 explains the model proposed for describing health of cotton plant. In section 3 contains information about the cotton crop disease dataset. In section 4 examines the experimental findings, and section 5 provides the conclusions.

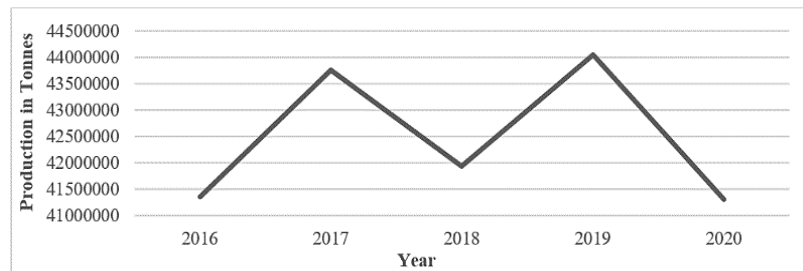


Figure 1. World production of cotton [1]

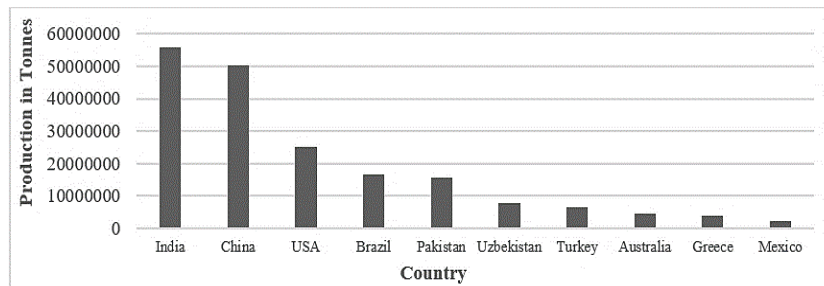


Figure 2. Top cotton producing countries [1]

2. PROPOSED METHOD

The Figure 3 shows the proposed encoder-decoder approach for describing health of cotton plant from an aerial image taken using drone or unmanned aerial vehicle. If the picture is captured from a long distance, it must be segmented into smaller parts in order to concentrate on the particular area of the image. The convolutional neural network (CNN) is an artificial neural network (ANN) that analyses patterns to recognise items and groups. The CNN serves as an encoder in the model, extracting features from an aerial picture of cotton fields. The output of pooling layer of CNN model is taken while last fully connected layer is not used to avoid loss of spatial information. The details of CNN models are provided below.

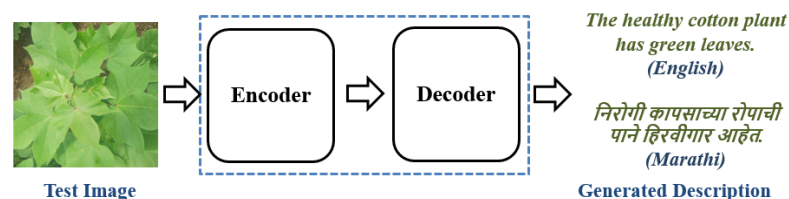


Figure 3. Proposed encoder-decoder approach for describing health of cotton plant

The decoder is provided with the features produced by CNN and their associated descriptions. The recurrent neural network (RNN) is another ANN that is commonly used for description generation. However, in the proposed framework, the long short-term memory (LSTM) network is used as a decoder because it solves the RNN's diminishing gradient problem [18]. During the training phase, the decoder learns how to generate a description for an image based on its characteristics and previously generated words. In this manner, a probability is given to each word based on its unique features and the preceding word. The step-by-step algorithm of the proposed approach is provided in Table 1. As we convert words into numbers in step 8 of the algorithm, the same algorithm can be used for generating captions in different language.

Table 1. Algorithm for proposed encoder-decoder approach

Sr. No.	Steps
1.	Image pre-processing.
2.	Building dictionary of image features by extracting features using CNN model. (By using output of pooling layer of CNN model. Last fully connected layer is not used to avoid loss of spatial information.)
3.	Caption pre-processing.
4.	Building dictionary of captions.
5.	Build vocabulary for the model by building dictionary of words by extracting words from dictionary of captions.
6.	Assign unique number for each word of word dictionary.
7.	Find maximum length of the caption from caption dictionary and make all captions of this length by padding end tokens, if it is necessary.
8.	Encode words of captions into unique numbers as assigned in word dictionary.
9.	Train the model to predict next word using image features and previous words.

CNN models: for feature extraction, experiments were performed using different pre-trained CNN architectures such as VGG-19 [19], InceptionResNetV2 [20], and EfficientNetV2L [21]. The visual geometry group (VGG) at the University of Oxford unveiled VGG-19, a CNN design, in 2014. The VGG-19 architecture has 19 layers, 16 convolutional layers and 3 completely linked layers. The convolutional layers are layered one after the other and have tiny 3×3 filters, resulting in very deep feature extraction. With 138 million parameters, the network is one of the frequently used deep learning networks.

InceptionResNetV2 model blends the inception and ResNet models. The InceptionResNetV2 model is based on the inception architecture, which captures features at various scales by combining convolutional layers with varied kernel sizes. The ResNet model is used to enhance deep neural network training by adding skip connections between layers. InceptionResNetV2 is a very deep network with 164 layers in total, and it improves its efficiency with a variety of sophisticated methods such as batch normalization, dropout, and weight decay. It has obtained very good accuracy rates on standard image classification standards such as ImageNet and has been used in a wide range of computer vision applications.

EfficientNetV2L is a CNN model that is part of the EfficientNet model family. It is intended to be computationally efficient while providing cutting-edge results on a variety of computer vision tasks such as image categorization, object recognition, and segmentation. EfficientNetV2L's "V2L" means for "vision to language," as this model is specially intended for multimodal activities that require comprehension of both visual and textual information. This is accomplished by integrating a pre-trained language model into the design. EfficientNetV2L uses the same compound scaling technique as EfficientNet, which includes scaling the model's depth, breadth, and resolution in a logical manner. When compared to other state-of-the-art models, this enables the model to reach high accuracy with fewer parameters and computation. The Table 2 shows the top-1 and top-5 accuracy of the CNN models on ImageNet validation dataset selected for experimentation [22]. The architecture's top-1 score shows that the predicted label matches the target label, whereas the top-5 score indicates that the target label is one of the top five anticipated labels.

Table 2. Accuracy of CNN models

CNN model	Top-1 score	Top-5 score
VGG-19	71.30	90.00
InceptionResNetV2	80.30	95.30
EfficientNetV2L	85.70	97.50

3. DATASET

The cotton disease captions dataset (CDCD) is developed to evaluate the performance of the proposed model. The dataset contains 3,112 colour images and each image is associated with a caption written in English and Marathi language. The 240 images are taken from Dhamodharan [23] while 2,293 images taken from Bhoi [24]. The remaining 579 images are captured at cotton farmland situated in Wardha District of Maharashtra

State, India using HENTJ Garuda 1080 drone by authors in year 2022. The drone has flying height of 55-60 meters and 1,080 p resolution.

The health of cotton plant is described for each image by an agronomist in English and Marathi caption. So the dataset contains 3,112 captions in English as well as 3,112 captions in Marathi language. The dataset contains images of cotton plant affected due to different disease such as aphids, army worm, bacterial blight, powdery mildew, and target spots along with images of healthy plant. The dataset contains images of diseases affecting only leaves and not stem, buds, flowers and boll. The images are collected from different sources and in different weathering condition hence the dataset is diverse. The Table 3 shows composition of CDCD.

Table 3. Composition of cotton disease captions dataset

Category	No of images
Aphids leaf	128
Army worm	115
Bacterial blight	119
Diseased cotton leaf	400
Diseased plants	921
Healthy and fresh cotton leaf	640
Healthy leaf	40
Healthy plant	514
Powdery mildew	119
Target spot	116

4. RESULTS AND DISCUSSIONS

The results of experimentation are evaluated on objective metric in section 4.1. To overcome the drawbacks of evaluation using objective metrics the subjective criteria is also used. The sections 4.2 discusses results on subjective criteria.

4.1. BiLingual evaluation understudy (BLEU) score for different CNN models

The proposed model's generated caption quality is validated using quantitative measures BiLingual evaluation understudy (BLEU). The BLEU measure is introduced by Papineni *et al.* [25] and it compares varying length phrase matches to the reference sentence using a weighted average. It counts the number of times an n-gram appears in the produced caption and the reference caption from the dataset, where an n-gram is a collection of one or more ordered words. The BLEU is a precision-based score ranging from 0 to 1, with a greater result indicating a superior match. For calculation of the score, the brevity penalty (BP) is calculated as,

$$BP = \begin{cases} 1, & \text{if } c > r \\ e^{(1-\frac{r}{c})}, & \text{if } c \ll r \end{cases} \quad (1)$$

where, c is the length of the generated caption and r is the reference caption length. The BLEU score is computed as,

$$BLEU = BP \cdot \exp(\sum_{n=1}^N w_n \log p_n) \quad (2)$$

where, p_n is modified n-gram precision, N is n-gram length, w_n is the positive weights and the sum of w_n is one.

By comparing generated caption to reference caption, the BLEU metric produces a number between 0 and 1 to show the quality of generated caption. The greater the number, the better the quality of the generated caption. The BLEU number is calculated for various N amounts. BLEU-1 employs a unigram precision number, whereas BLEU-2 employs a geometric sum of unigram and bigram precision. The geometric average of unigram, bigram, and trigram precision is used in the BLEU-3, while the geometric average of unigram, bigram, trigram, and four-gram precision is used in the BLEU-4. The Table 4 shows the results on BLEU metrics for various CNN models. On all four BLEU measures, the efficiency improves from VGG-19 to InceptionResNetV2 to EfficientNetV2L. The BLEU score obtained for captions generated in English and Marathi language is also comparable.

Table 4. Results on BLEU metrics for different CNN models

CNN model	Language of caption	BLEU-1	BLEU-2	BLEU-3	BLEU-4
VGG-19	English	0.79	0.75	0.72	0.69
	Marathi	0.78	0.75	0.73	0.68
InceptionResNetV2	English	0.86	0.80	0.77	0.74
	Marathi	0.86	0.81	0.76	0.72
EfficientNetV2L	English	0.90	0.83	0.81	0.78
	Marathi	0.89	0.84	0.78	0.75

4.2. Results for different CNN models on subjective criteria

The objective metrics simply compare the generated caption to the reference captions to calculate a number that shows the caption’s quality. This results in a high score for grammatically wrong captions if only a few words fit the terms in reference captions. Furthermore, each person has a unique way of explaining a picture, which cannot be handled by comparing produced captions with a limited number of reference captions. As a result, the quality of the generated description is carefully validated by an impartial agronomist who is also fluent in English and Marathi languages. Based on the content, the generated description is classified into one of three categories: correct caption, partially correct caption, and incorrect caption.

The Table 5 shows the results on subjective criteria for different CNN models. For efficientNetV2L model, 87.76% captions are categorized as correct compared to 84.29% for InceptionResNetV2 and 76.89% for VGG-19 model when caption are generated in English language. For Marathi language, 86.70% captions are categorized as correct for EfficientNetV2L while 84.98% for InceptionResNetV2 and 76.00% for VGG-19 model. Overall, from VGG-19 to InceptionResNetV2 to EfficientNetV2L, efficiency improves.

Table 5. Results on subjective criteria for different CNN models

CNN model	Language of caption	Correct caption (%)	Partially correct caption (%)	Incorrect caption (%)
VGG-19	English	76.89	15.22	7.89
	Marathi	76.00	15.03	8.97
InceptionResNetV2	English	84.29	11.69	4.02
	Marathi	84.98	10.02	5.00
EfficientNetV2L	English	87.76	10.65	1.59
	Marathi	86.70	10.84	2.46

The performance of different CNN models for English and Marathi language on subjective criteria is compared in Figure 4. Similar to BLEU score, the performance of different models for English and Marathi language is comparable. The InceptionResNetV2 and EfficientNetV2L models have provides substantially better performance compared to VGG-19 which is considered as a shallow model due to less number of layers.

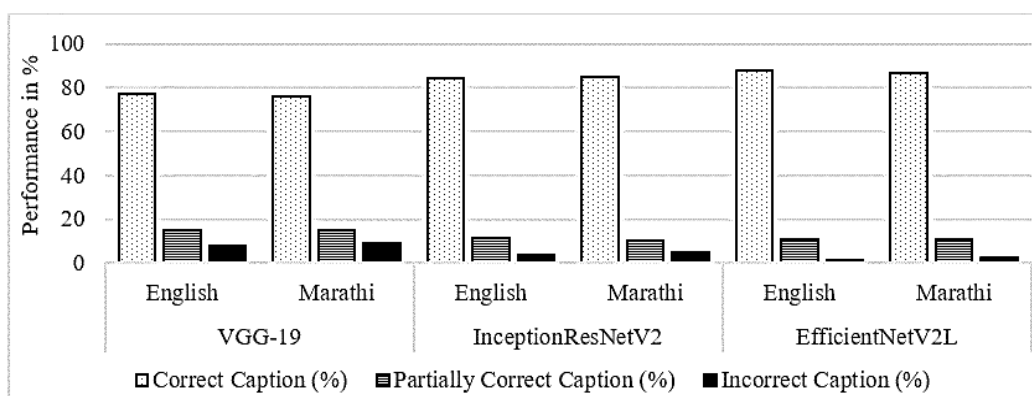


Figure 4. Comparison of performance of different CNN models on subjective criteria

If the caption correctly describes health of the cotton plant with no grammatically error, then it is categorized into correct caption category. The Figure 5 shows the healthy cotton plant is described properly by caption generated in English language. If the generated caption is wrong, grammatically incorrect and meaningless then it is categorized in incorrect caption category. The Figure 6 shows the cotton plant which is

actually affected by powdery mildew fungal disease but the caption generated in Marathi language failed in identifying it. Moreover, the generated caption is meaningless and grammatically incorrect.



Reference Caption:

The healthy cotton plant has green leaves.

Generated Caption:

The healthy cotton plant has fresh green leaves.

Figure 5. Example of correct caption in English language generated by EfficientNetV2L CNN model



Reference Caption:

कापसाच्या रोपाची पाने पांढऱ्या बुरशीजन्य रोगाने प्रभावीत आहेत.

Generated Caption:

कापसाच्या रोपावर बर्फ आहे.

Figure 6. Example of incorrect caption in Marathi language generated by InceptionResNetV2 CNN model

The caption which correctly describes the health of the plant in broader sense, grammatically proper but either hides the specifics or with incorrect disease identification then it is categorized in partially correct caption category. The Figure 7 shows the cotton plant affected by aphids. The generated caption correctly identifies that the plant is diseased and needs treatment but fails to identify the type of disease.



Reference Caption:

The aphids have damaged cotton plants by sucking the juice from leaves.

Generated Caption:

The cotton plant is in a diseased condition and needs treatment.

Figure 7. Example of partially correct caption in English language generated by VGG-19 CNN model

The foliar disease target spots have affected the plant shows in Figure 8. The caption generated in Marathi language for corresponding image identifies that plant is unhealthy however specifies disease as bacterial blight. There are several instances where model fails to distinguish between target spot and bacterial blight diseases similarly between aphids and powdery mildew disease due to less interclass similarity.

**Reference Caption:**

पानांवरील बुरशीजन्य काव्या
ठिपक्यांमळे कापसाच्या रोपाचे
नुकसान झाले आहे.

Generated Caption:

जिवाणूजन्य आजारामुळे
कापसाच्या रोपाची पाने खराब
झाली आहे.

Figure 8. Example of partially correct caption in Marathi language generated by EfficientNetV2L CNN model

5. CONCLUSIONS

In this paper, an encoder-decoder model for describing health of cotton crop using a caption in English and Marathi language from an aerial image is proposed. The CNN acts as an encoder while LSTM works as a decoder in the model. The CDCD, which has 3,112 images and associated captions in English and Marathi language was developed for evaluation of the algorithm. Images of cotton plants in various states of health can be found in the dataset. It includes plants that have been affected by a variety of ailments, including aphids, army worms, bacterial blight, powdery mildew, and target spots. The EfficientNetV2L has outperformed InceptionResNetV2 and VGG-19 CNN models on BLEU scores as well as on subjective criteria. It has achieved 0.90 and 0.89 BLEU-1 scores for captions generated in English and Marathi language respectively. The 87.76% captions generated in English language are categorized as correct on subjective criteria compared to 86.70% captions generated in Marathi language. The performance of the model in generating English as well as Marathi captions is comparable. Due to lower interclass similarity, the model has had trouble differentiating between target spot and bacterial blight illnesses, as well as between aphids and powdery mildew disease. By building large dataset, the challenge of interclass similarity can be addressed.




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