

THE HYBRID CLASSIFICATION SCHEME FOR PLANT DISEASE DETECTION IN IMAGE PROCESSING

Kunal Tripathi

Research Scholar

DECLARATION: I AS AN AUTHOR OF THIS PAPER / ARTICLE, HEREBY DECLARE THAT THE PAPER SUBMITTED BY ME FOR PUBLICATION IN THE JOURNAL IS COMPLETELY MY OWN GENUINE PAPER. IF ANY ISSUE REGARDING COPYRIGHT/PATENT/ OTHER REAL AUTHOR ARISES, THE PUBLISHER WILL NOT BE LEGALLY RESPONSIBLE. IF ANY OF SUCH MATTERS OCCUR PUBLISHER MAY REMOVE MY CONTENT FROM THE JOURNAL WEBSITE. FOR THE REASON OF CONTENT AMENDMENT/ OR ANY TECHNICAL ISSUE WITH NO VISIBILITY ON WEBSITE/UPDATES, I HAVE RESUBMITTED THIS PAPER FOR THE PUBLICATION. FOR ANY PUBLICATION MATTERS OR ANY INFORMATION INTENTIONALLY HIDDEN BY ME OR OTHERWISE, I SHALL BE LEGALLY RESPONSIBLE. (COMPLETE DECLARATION OF THE AUTHOR AT THE LAST PAGE OF THIS PAPER/ARTICLE)

Abstract

Efficiency in horticulture is crucial for economic growth. The presence of illness in plants is quite common, which is one reason why a recognising plant disease is important in the field of farming. In the unlikely event that essential safety precautions are not observed, plants may suffer major repercussions that have an impact on the effectiveness, quantity, or quality of the comparative commodities. For instance, the US is home to pine trees that are defenceless against the dangerous illness known as small leaf disease. How to detect and classify capsicum illnesses Capsicum is shown to be contaminated by various bacterial, infectious, and infection illnesses using image processing technique, and these disease side effects are discernible through infected leaves. By using a pre-programmed technique, it is possible to identify plant illnesses, which is beneficial since it reduces the laborious task of monitoring vast ranches' harvests while also seeing disease symptoms early on. Using the k-implies grouping approach, the contaminated area of the capsicum is eliminated. Then, surface components, or GLCM highlights, are separated for this contaminated area. Support vector machines may be used to describe various bacterial/contagious capsicum illnesses using these components.

Keywords: *Capsicum Diseases, Hybrid Classification, Image Processing, Plant Disease, Vector Machines*

1. INTRODUCTION

The vast expanse of landfills is now seen as more than just a source of food. India's economy is heavily reliant on agricultural output. So, it's critical to understand plant diseases in the agricultural sector. For spotting a plant disease in its early stages, it is beneficial to use a programmed disease location innovation. For instance, pine trees in the US are susceptible to a dangerous illness known as small leaf disease. The troubled tree grows slowly and dies in six years or less. Georgia and other Southern US states are affected, as well as Alabama. In these cases, early disclosure could have been beneficial. As per the flow technique for disease discovery in plants, experts may now discern and recognise plant concerns using simply their own unassisted eyes. This calls both a substantial team of specialists and ongoing plant observation, both of which are quite expensive when running enormous ranches. In the meanwhile, ranchers in certain nations want access to sufficient resources and even understand they may consult qualified specialists. Expert counselling is therefore expensive and time-consuming. [1] The suggested method for keeping an eye out for enormous fields of crops performs excellently in these circumstances. So, it is easier and less expensive to differentiate illnesses based only on their effects on plant leaves. Moreover, it supports machine vision, which may be used to drive robots in clear-cut circumstances and provide image-based programmed process control and evaluation. But, using a programmed identification approach will take less effort, less time, and produce a far higher degree of accuracy. Plants are susceptible to common bacterial, viral, parasite diseases including brown and yellow spots, early and late singe, and others. Image processing is utilised to quantify the area affected by the disease and determine how the colour of the affected area contrasts.

Image division is the process of dividing or classifying a picture into multiple regions. Right now, image division should be achievable in a number of methods, from the simple straight thresholding method to the sophisticated variety image division techniques. In general, these components are comparable to anything that people can certainly separate into independent items and see. As Computers are unable to view objects clearly, there are several methods for dividing up photos. The division approach was chosen because of the image's different features. To segment coloured pictures, we need a hereditary computation. This might be a variety range, framework, or part of the image.

A few applications of image-based processing are used in horticulture, such as the precise and early detection of plant diseases. The most crucial step in computerised image processing is enhancing interesting visual highlights, after which significant data is acquired from the improved image for additional processing. The designers of depict created a specialised framework for locating plant diseases by employing informative and graphical ways of representation. The framework gives the customer access to a few techniques for identifying and managing plant diseases [2]. Distribution shows a method for classifying and discovering diseases in potato leaves based on neural networks. The obscure leaf that will be examined to determine if it is healthy or sick is distinguished and grouped using a back propagation neural network (BPNN) with an accuracy of 92%. Division computation is used in the picture division process.

Before they reach development, infections in the leaves of organic foods, citrus, wheat, and rice can significantly reduce their yields. This necessitates the rapid and accurate identification of leaf diseases in natural goods, such as citrus, wheat, and rice, as well as the early delivery of a customised remedy. Due of the vast area, human examination-based diagnosis of leaf diseases is severely constrained, and a model that can address this problem is urgently needed. When a particular type of leaf disease is identified, the real plant often has its own ID model. There will be a problem with capacity if each sickness of organic foods, citrus, wheat, and rice has its own acknowledgement model. The ability to carry out diverse jobs enables components to cooperate and support one another. As a result, it is possible to improve model accuracy while reducing the need for storage for the leaf disease recognition models. For this, a model must be developed that can recognise and examine leaf diseases in organic foods, citrus, wheat, and rice.

2. REVIEW OF LITREATURE

Karthik et al. 2020 provided a plan to group crucial elements for spotting illness in tomato leaves in light of previous learning. Their suggested approach makes use of the three illnesses-covering Plant Village dataset and CNN-learned highlights. They had 98% accuracy on the approval sets after several cross-approvals.

The CNN model was created by Sharma et al. in 2020. When tested on unlabeled data, the S-CNN model performed better than the F-CNN model, drastically increasing its display to 98.6% exactness.

Sambasivam and Opiyo 2020 suggested a method for identifying cassava leaf disease in their investigation. They had the potential of achieving an exactness score of more than 93% by using class weight, the Created Minority Oversampling Method, and a deep CNN generated without any prior planning.

In accordance with Mama et al. 2017, they utilised VGG to identify and control four illnesses that harmed cucumber leaf leaves and adversely affected crops. A significant number of plant leaf pictures were subjected to the classification cycle in order to identify the presence or early stages of illness in the leaves.

Too et al. 2021 used four transfer learning (TL) models to rank the absence and presence of illness in plant leaves. These parts included the VGG16, early V4, ResNet, and DenseNet structures. DenseNet provides more pertinent results with a faster processing time as compared to other types.

He also assessed 12 different plant species that were used to categorise the presence or absence of illness in plants in a previous paper published in 2019

Kaya et al. 2019 used TL for deep NNs to study datasets including Flavia, Swedish, and UCI Leaf to describe plants. In this way, Singh et al 2019 's proposal for a programmed classification technique focused on the leaves of a maize plant using a powerful NN model.

The focus by Dhivyaa et al. 2022 uses an enlarged intricacy network and other thick blocks to select the right parts in view of bidirectional long transient memory (Bi-LSTM) to discover plant illnesses. Data from Plant Village and the cassava disease have demonstrated the viability of their suggested paradigm. They discovered that the suggested model for identifying cassava leaf disease had a very high F1 score of 95.49 percent.

A lightweight convolution neural network with several consideration modules was used in a study by Bhujel et al. in 2022 to enhance the models' display. They had the choice to create their models using information on tomato leaf diseases. The models' presentation was estimated

using the standard classification precision metrics (F1 score, exactness, and review). With a 99.69% normal, the convolution block centre module exhibited the highest level of accuracy.

3. Materials and Methods

a) Dataset Description

Images of both healthy and unhealthy capsicums are included in the image data set. Throughout the growing season, capsicum crops were inspected for symptoms of a disease associated with capsicums throughout Shimla and the Solan area. To achieve the greatest results, each image is taken with a top-tier computerised camera with a 16 uber pixel goal and saved in the jpeg format[3]. The picture information base has a total of 70 photos, including 30 of healthy capsicum and 40 of sick capsicum with anthracnose, bacterial spot, cercospora leaf spot, dark leaf spot, and fine mould.



Figure 1: A healthy pepper, a healthy pepper leaf, and a sick pepper with bacterial canker disease are some examples from the dataset. (d) Bacterial Spot Diseased, Viral Infected Capsicum (e) Capsicum leaves with bacterial spots (f) Capsicum leaves with Gray-leaf spot symptoms (g) Capsicum leaves with anthracnose symptoms (h) Capsicum leaves with Cercospora-leaf spots (h).

Capsicum is one of the most notable and commonly consumed vegetables, and it is also one of the richest sources of vitamins A and C. It is consumed raw or cooked in various dishes, such as a platter of mixed greens. The scientific or botanical name of the pepper is *Capsicum annuum*; additional common names are Shimla mirch, sweet pepper, ringer pepper, and green

pepper. [5] Capsicum offers several health advantages, including promoting skin health, fighting illness, bolstering the immune system, and being beneficial for diabetes people. Capsicums can be grown inside, outdoors, in pots, or in other containers.

Between 18 and 30 C is the best temperature range for producing capsicums. They should be planted on raised beds or soil that has been depleted in a place that receives full light for the most of the day. Like other crops, capsicum is susceptible to a wide range of diseases and infections. The two bacterial/contagious contaminations that affect capsicum are shown below.

Figure: 2 A bacterial blister is a little elevated white patch with an earthy-colored environment that appears on plants. As shown in Fig. 2, on a natural goods little roundabout, slightly elevated sores with an earthy coloured community and a white brilliance should be discernible.



Figure 2: Bacterial canker symptoms on the capsicum and its leaf

Bacterial spot: Bacterial spots can have negative impacts on a plant's stem, natural product, or leaves. This disease manifests on leaves as small, spherical lesions that are yellow-green with a yellowish corona and a brown or black centre. The adverse impacts on organic goods manifest as green, prolonged, hardly elevated dots that eventually become brown, as seen in Fig 3.



Figure 3: Infected capsicum had a bacterial spot.

Anthracnose: As seen in Fig. 4, irregularly formed earthy coloured patches with dark earthen coloured margins appear on leaves, while circular wounds form on young organic material.

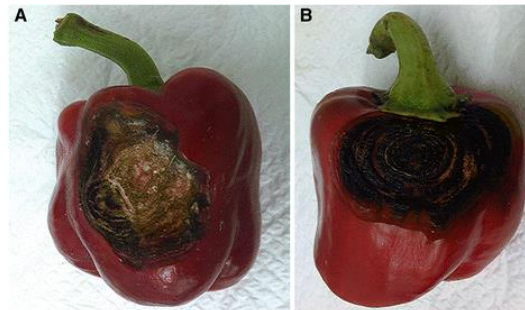


Figure 4: Anthracnose-affected capsicums

Cercospora leaf-spot: There are circular areas with a low light focus and a reddish earthy boundary. Afterwards, as seen in Fig. 5, these spots turn brown with a dull ring and a yellowish corona around the ring, giving them the appearance of "frog eyes."



Figure 5 : the Cercospora leaf-spot

Dark leaf spot: The illness is mostly identified by a small spot that might be red or brown in colour. Afterwards, various areas on the passages cause these spots to grow white centres with red or earthy coloured borders, and they become yellow and drop.

b) Software used

The images that were collected for our dataset are processed using a variety of techniques using the Matlab 2018b programming platform. [6] A graphical user interface (GUI) is created using MATLAB, taking into account the identification and categorization of various capsicum illnesses.

c) Proposed Methodology

The strategy used in the presented study is discussed below, and Fig. 7's block diagram shows the many operations. The outstanding images of capsicum plants—both healthy and sick—used in this study were shot using a camera and received from residents of the farming communities in Shimla and the Solan area. Certain visual properties that are crucial for further processing are enhanced during the pre-processing step, whereas unneeded or irrelevant distortion is minimised. [7] Images are reduced to 256 256 pixels in size, a fixed resolution, to save the processing strain. Pre-processing includes picture resizing, color-space conversion, and image enhancement to draw attention to certain elements. These photographs' contrast is boosted via histogram equalisation, which enhances the image's clarity and general quality.

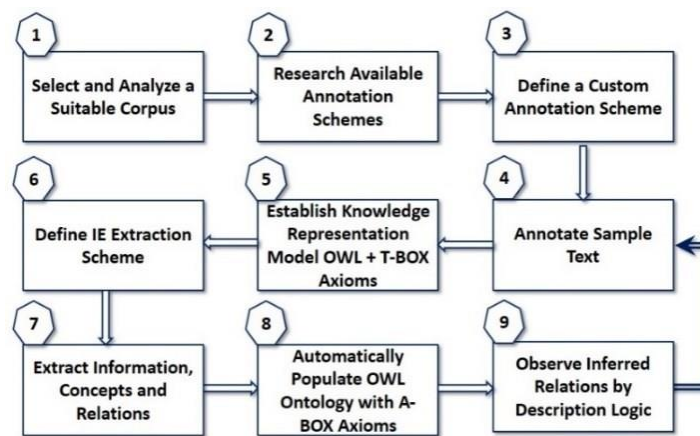


Figure 6: Methodology for the proposed work

Image division separates or splits a picture into portions to make it easier to understand. This technique is regularly employed to identify boundaries or items in a picture. Information can be divided in a variety of ways, such as division in view of district, division in view of edges, and division in view of bunching. The K-implies bunching computation, which separates the information into k groups with each information value having a position in the bunch with the closest mean, is one of the most well-known grouping calculations for division assignments.

Component extraction, the process of transforming input data into a significant arrangement of qualities, is essential for differentiating between objects belonging to one class and those belonging to another. The three most well-known methods used for highlight extraction are surface-based, variety-based, and shape-based. FE is a crucial step in the process of removing

the components from an image's intriguing setting. The surface of the picture may be identified by its hardness, roughness, and variety distribution over the entire image.

The five surface highlights of differentiation, connection, entropy, energy, and homogeneity are processed for the sound/ill capsicum used as the classifier's feedback. The power contrast between a pixel and its neighbour throughout the entire image is considered to be differentiation. The following is a representation of these properties. Contrast decreases to zero for a stable picture. The relationship between a pixel and its neighbouring pixels throughout the entire image is approximated using connections. Its value is 1 for favourably related pictures and -1 for negatively associated images. Relationship scope: [-1 1]. Since homogeneity is a percentage of energy, a picture contains more energy the more homogeneous it is. In the odd occasion that the energy value is closer to 1, the picture is expected to be constant. Range = [0 1]. Entropy is a measurement of how eccentric or problematic a space is. Homogeneity, which is used to measure pixel resemblance, is evaluated using an inclining dark level co-event network and produces a homogeneity of 1. A corner-to-corner GLCM has a range of one.

An urgent phase is the categorization of the information into groups that direct in the identifiable proof of the illness kind. In this review, a double classifier known as the Support Vector Machine (SVM) is used to find the classes that are strongly connected with the realised classes using directed learning. By using the preparation data, the support vector machine creates the best partition hyper plane between the classes.

The separated component dataset is used as training data to enable the SVM preparing classifier to differentiate between images of healthy and sick capsicums. The true positive rate (TPR) and false positive rate (FPR), two metrics that are used to evaluate the classifier's presentation, are calculated as follows.

TPR measures the accuracy with which sick leaves are identified.

$$\text{TPR} = \text{TP} / (\text{TP} + \text{FN})$$

The FPR measures how quickly healthy leaves are replaced by sick ones.

$$\text{FPR} = \text{FP} / (\text{FP} + \text{TN})$$

Specificity:

$$\text{Specificity} = \text{TN} / (\text{TN} + \text{FP})$$

Accuracy: The percentage of healthy and sick leaves that are appropriately categorised as normal or diseased.

$$\text{Accuracy} = (\text{TP} + \text{TN}) / (\text{TP} + \text{TN} + \text{FP} + \text{FN})$$

4. Results and Discussions

The objective of the study effort that has been provided is to identify and categorise healthy or sick capsicum plants for a few selected bacterial and fungal illnesses. MATLAB platform 2018b was used in the study to create algorithms on several images of both healthy and sick capsicum.

a) Pre-processing and segmentation results:

The pre-processed image in Fig. 8 (b) shows how histogram equalisation has enhanced the image's contrast. Image 9 shows the segmented picture that amply demonstrates the diseased portion of the capsicum leaf (c).



Figure 7: (a) Original image, (b) Enhanced image, (c) Segmented image

b) Feature extraction results:

The five fundamental components—contrast, relationship, energy, entropy, and homogeneity—are removed and extracted from the wiped out affected portion of the capsicum. The normal upsides of the attributes that were extracted from sound and sick capsicums and their leaves are shown in Table 1; utilising these average values, a feature dataset that assists in further classification is constructed. [10] To identify between healthy and unhealthy plants, the assessed image's properties should fall inside the range of values in our feature collection.

			Texture Features (Average Values)
--	--	--	------------------------------------

Affect ed plant	Normal/Di seased	Disease Name	Contr act	Correla tion	Ener gy	Entro py	Homoge neity
Capsic um	Normal Diseased	Anthrac nose	2.136	1.569	3.156	8.561	1.895
Leave s	Normal Diseased	Bacteri a spot	3.125	3.189	4.256	5.125	1.999
		Cercosp ora leaf-spot	12.36	4.596	3.896	5.987	2.156
		Gray leaf spot	3.125	5.128	5.125	4.893	3.978
		Powder y mildew	4.855	5.789	6.555 6	7.996	8.125
			4.256	5.888	7.256	7.886	4.256
			4.256	6.256	8.255	9.366	8.256

Table 1: Average Values of feature for normal and diseased capsicum plant

The following inferences may be made from table 2: Energy = 2.999, Correlation = 2.365 and Contrast = 1.2563 Entropy equals 3.125 The feature ranges for a typical capsicum texture are homogeneity = 2.963.

The following feature ranges apply to a typical capsicum leaf: Correlation: 3.245 contrast: 1.236 kcal = 0.3.245 Entropy equals 4.896 whereas homogeneity is 3.899.

The following are the sick capsicum's textural feature ranges: Energy is 2.984, entropy is 3.889, contrast is 0.3830, correlation is 0.7736–0.9377, and homogeneity is 5.255.

c) Classification results:

Using the four classifiers, our preparation data is divided into two categories, specifically sound and sick. The classifier with the best precision outcomes is chosen for classification. SVM and KNN provide classifier outputs with 100% accuracy (table 3). [11] Since the data comprises precisely two classes, as stated in the application/issue articulation, SVM may be used to divide capsicum into two categories: solid and diseased. SVM is used in this instance to divide the peppers into two groups.

Features	Classifiers	Accuracy
GLCM	Tree	32.33
	Linear	40.22
	Discriminate	
	SVM	44.58
	KNN	50.33

Table 2: Classifiers Results

Using the four classifiers, our preparation data is divided into two categories, specifically solid and diseased. The classifier with the best exactness outcomes is chosen for classification. SVM and KNN provide classifier outputs with 100% accuracy (table 3). [12] The application/issue statement states that when the information includes precisely two classes, SVM may be used to classify capsicum into two groups, healthy and ill. SVM is used in this instance to divide the peppers into two groups.

Parameters	No. of image
True positive values	30
False negative values	54
True Negative values	50
False positive values	61

Table 2: Confusion Matrixes

Parameters	Result
------------	--------

Accuracy	100%
Result	100%

Table 3: Parameters

5. CONCLUSION

The proper identification and categorization of plant diseases, which may be accomplished using image processing techniques, is essential for the growth of a good harvest and to increase crop output. In this study, the diseased afflicted section of the capsicum is first broken apart, and then highlight extraction is used to separate the components of the contaminated part. [13] Finally, an SVM classifier is used to classify the disorders associated with capsicum. To identify illness and describe solid/diseased capsicum and its leaves, the suggested arrangement is tested for the five diseases, specifically anthracnose, bacterial spot, fine accumulation, cercospora leaf-spot, and dim leaf-spot. A SVM classifier can discriminate between solid and diseased capsicum with an accuracy of about 100%. Eventually, using multi-class classifiers, contaminated capsicum may also be divided into illness types, such as bacterial or parasite diseases.

6. FUTURE SCOPE

Eventually, using multi-class classifiers, contaminated capsicum may also be classified according to the type of illness, either bacterial or infectious. The suggested method classifies healthy and ill capsicums into two groups. [14] This research can only currently detect five capsicum contaminations. Moreover, this investigation may be expanded to include additional capsicum contaminations and to identify and classify a variety of ailments associated with other expensive natural items or goods. The suggested framework is currently autonomous, but in the future, an android-application based setup that is available to farmers or anybody with a web connection may be established, allowing farmers to reliably identify crop diseases at an early stage.

REFERENCES

1. Pinaki Chakraborty, Dilip Kumar Chakrabarti, “A brief survey of computerized expert systems for crop protection being used in India”, ELSEVIER-ScienceDirect, Vol. 18, pp. 469-473, 2008.
2. Tai A. P., Martin M. V., , and Heald C. L. (2014). Threat to future global food security from climate change and ozone air pollution. *Nat. Clim. Chang* 4, 817–821. 10.1038/nclimate2317
3. Lee H.Y., Kim D.H., Park K.R., 2019. Pest diagnosis system based on deep learning using collective intelligence. *The International Journal of Electrical Engineering & Education*, p.0020720919833052.
4. Singh V., Misra A.K., 2017. Detection of plant leaf diseases using image segmentation and soft computing techniques. *Information Processing in Agriculture*, 4(1), pp.41–49.
5. Zhang S., Wu X., You Z., Zhang L., 2017. Leaf image based cucumber disease recognition using sparse representation classification. *Computers and electronics in agriculture*, 134, pp.135–141.
6. Sladojevic S., Arsenovic M., Anderla A., Culibrk D., Stefanovic D., 2016. Deep neural networks based recognition of plant diseases by leaf image classification. *Computational intelligence and neuroscience*, 2016.
7. Rumpf T., Mahlein A.K., Steiner U., Oerke E.C., Dehne H.W., Plümer L., 2010. Early detection and classification of plant diseases with support vector machines based on hyperspectral reflectance. *Computers and Electronics in Agriculture*, 74(1), pp.91–99.
8. Barbedo J. G. A., Tibola C. S., Fernandes J. M. C. (2015). Detecting fusarium head blight in wheat kernels using hyperspectral imaging. *Biosystems Engineering*, 131, 65e76.
9. Zhou R., Kaneko S., Tanaka F., Kayamori M., Shimizu M. (2014). Disease detection of Cercospora Leaf Spot in sugar beet by robust template matching. *Computers and Electronics in Agriculture*, 108, 58e70.
10. Mahlein A.K., Oerke E.C., Steiner U., Dehne H.W., 2012. Recent advances in sensing plant diseases for precision crop protection. *European Journal of Plant Pathology*, 133(1), pp.197–209.

11. Arivazhagan S, Shebiah RN, Ananthi S, Varthini SV (2013) Detection of unhealthy region of plant leaves and classification of plant leaf diseases using texture features. *Agric Eng Int CIGR J* 15(1):211–217.
12. Kruse OMO, Prats-Montalbán JM, Indahl UG, Kvaal K, Ferrer A, Futsaether CM (2014) Pixel classification methods for identifying and quantifying leaf surface injury from digital images. *Comput Electron Agric* 108:155– 165.

Author's Declaration

I as an author of the above research paper/article, hereby, declare that the content of this paper is prepared by me and if any person having copyright issue or patent or anything otherwise related to the content, I shall always be legally responsible for any issue. For the reason of invisibility of my research paper on the website/amendments /updates, I have resubmitted my paper for publication on the same date. If any data or information given by me is not correct I shall always be legally responsible. With my whole responsibility legally and formally I have intimated the publisher (Publisher) that my paper has been checked by my guide (if any) or expert to make it sure that paper is technically right and there is no unaccepted plagiarism and the entire content is genuinely mine. If any issue arise related to Plagiarism / Guide Name / Educational Qualification /Designation/Address of my university/college/institution/ Structure or Formatting/ Resubmission / Submission /Copyright / Patent/ Submission for any higher degree or Job/ Primary Data/ Secondary Data Issues, I will be solely/entirely responsible for any legal issues. I have been informed that the most of the data from the website is invisible or shuffled or vanished from the data base due to some technical fault or hacking and therefore the process of resubmission is there for the scholars/students who finds trouble in getting their paper on the website. At the time of resubmission of my paper I take all the legal and formal responsibilities, If I hide or do not submit the copy of my original documents (Aadhar/Driving License/Any Identity Proof and Address Proof and Photo) in spite of demand from the publisher then my paper may be rejected or removed from the website anytime and may not be consider for verification. I accept the fact that as the content of this paper and the resubmission legal responsibilities and reasons are only mine then the Publisher (Airo International Journal/Airo National Research Journal) is never responsible. I also declare that if publisher finds any complication or error or anything hidden or implemented otherwise, my paper may be removed from the website or the watermark of remark/actuality may be mentioned on my paper. Even if anything is found illegal publisher may also take legal action against me

Kunal Tripathi