A Vision Based Approach For Anomaly Detection In Smart Environments Using Thermal Images

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Abstract*: A process of identifying, accumulating the infrared heat radiation into a form of visible images which in turn forms a thermal images. These thermal images are useful for anomaly detection in critical applications. Infrared radiations from the objects vary from each other considering the environmental conditions. Heat maps can be generated based on the amount of heat radiation collected. Those generated heat maps can be analyzed using image processing approaches. In this paper, an attempt has been made to identify or predict possible outbreak of fire due to very high heat emission by objects using thermal images for any environment. Required features from the acquired thermal images are extracted using image processing algorithm for analyzation. Using extracted features, decision tree classification is used to detect anomaly. Experimental results show promising direction to detect anomaly towards disaster management. Using the proposed method 91% of accuracy was obtained in detecting possible fire break out.

Index Terms*: Decision Tree, Feature Extraction, Thermal Infrared Imaging.

I. INTRODUCTION

Thermal cameras and imaging have periodically been in interest mainly for smart environments, military applications. Increasing amount of image quality and resolution since last few years have however, unlocked new challenges and application areas in thermal imagery. Thermal cameras are useful to measure a temperature difference. These cameras are advantageous compared to cameras operating in the visual spectrum due to their ability to acquire images in complete night, robust to lighting variations and less interruption on privacy, as tempering is tedious.

Thermal imaging is the most relevant for finding problems or possible problems in a diversity of applications across many fields. Infrared images are radiometric data stored or encrypted with a proprietary file format (.IMG, .JPG, .IS2, .IRI, .TIF, .SIT, .ANA, .FTS, etc.). Many older file formats are merged with each other and no longer being supported to camera manufactures. The data that are stored in these image files becomes unattainable due to this. The user will find minor differences at a greater distance with a high resolution camera. A considerable problems missed with a lower resolution camera can be found by user. For example, a switch board having a component which overheats; a thermal imager will instantly find that hot spot. Most infrared cameras have fewer pixels than visible light cameras. A sharper thermal images of smaller targets from far distance can be measured by high resolution infrared cameras.

All objects emit infrared energy, but the level of emission varies depending on the object's surface. Emissivity is measured on a scale of 0–1, must be matched to the material and surface condition to produce accurate temperature measurements from imager.

In this paper, we propose a vision based approach to detect anomalies in environments using thermal images. The paper is organized as follows. The second section presents the methods and materials used. Additionally, the proposed technique for anomaly detection from thermal images, followed by the experimental results. Finally the last section gives conclusion and future work that can be done to improve this work.

II. LITERATURE SURVEY

Thermal cameras are used to overcome the problem of varying lighting conditions [1]. Wilfried et al. have used Principal Component Analysis (PCA) for object detection which is based on machine learning for image classification. Wilfried et al. have compared, analyzed and evaluated multiple algorithms; and have used the AdaBoost machine learning algorithm for object detection, Euclidean and Mahalanobis distances for classification and Gaussian classifier and Mahalanobis distances for object detection. To perform anomaly detection, background subtraction has been used; background subtraction technique has been employed for classifying samples which are not fit in to the background as foreground or anomalies, to determine RoI (Region of Interest) which is necessary for detecting specific objects. Detection based on thresholding might not work for instances like camouflage, reflection, and versatile background [2].

For object classification and detection, feature enhancement has been used in [3]. Thermal images lack texture and color information. A gradient-based method for feature enhancement in thermal images have been proposed by Zelin et al. [3] with statistical analysis on gradient magnitudes of foreground images. Object features are formulated with gradient saliency, under different environmental conditions

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thermal images can be captured for different objects which emit or reflect the radiation. Restricted information has been provided from signal-to-noise ratio of thermal image for performing detection tasks. A complex background context, coarse gray-level foreground objects and huge unexpected noise can be introduced in thermal images. A binary thinning foreground counter (TFC) has been used to find superfluous information of background and noise. Histogram processing is used for the gradient image. To recognize the binary image where contour points are linked from few disconnected contour segments, Zelin et al. have used Connected Component Algorithm (CCA) on the OSU-Thermal Pedestrian dataset and developed a robust gradient-based approach for object contour enhancement in thermal image under different environments. Low-level features have been used for detecting parts of the human body. The classification process is in three stages: head modeling, human modeling, and classifier. Modified HOG (Histogram of Oriented Gradients) algorithm has been used on IR images database. A Wuhan-Guide TP8 IR camera has been used to capture thermal images for the experiment. For Gaussian filter to calculate the gradient of foreground image, Zelin et al. have set standard variance at 0.75 which has given robustness and flexibility [3].

A collection of features which explain water permeation and heating or cooling properties, S. Budzan has exploited long wave infrared (thermal) imagery for material classification [4]. According to Planck's blackbody radiation law, all objects which emit infrared radiation can be detected by Long Wave Infrared (LWIR) camera. Characteristic Model of Permeation (CHAMP) models the water permission with a method to take out the heat equation constant; results have been presented with graph for precision and recall values where short distance detection has better results in [4].

To detect the presence of a human on the thermal image, Philip et al. [5] have computed Fast-Fourier Transform (FFT) of a binned spherical mapping of the CHAMP with Haar-Cascade classifier method. Object detection deals through Haar-Cascade method comprises: Haar like features, Integral images, Adaptive Boosting or AdaBoost, and Cascade Classifier Combination. When an object is hidden behind some obstacle or at the back of another object, the technique of object detection based on visual imagery fails; Christian et al. [6] have developed an object classification method using the record of heat signature; and shown a graph for different background vs precision and recall where recall value is more than precision for each background. Every object has its radiation pattern and emits infrared energy (heat) as a function of temperature; and have used an averaging filter and a median filter to remove noise from thermal images [7]. A. K. Bhartee et al. [7] obtained correct output 15, 20 and 11 for respective Human, Animal and Natural thermograph from 20 inputs with the overall success rate 76.67%.

From the available classification techniques such as Neural Networks, Support Vector Machine (SVM) [8], KNN (K-Means) and Decision Tree, Bhaskar et al. [9] have plotted graphs for attribute vs complexity and attribute vs accuracy using KNN and Decision tree techniques where authors got better results for Decision Tree technique when number of attributes increases. The complexity and accuracy are 80% and 95% respectively for classification [9]. Brijain et al. [10] have shown application of decision tree with comparison between different algorithms such as ID3, C4.5, C5.0 and CART and concluded that the performance of the algorithm depends on entropy, information gain and features of data. Huang et al. [11] have combined principle of Taylor formula with information entropy and simplifies the solution of ID3 algorithm with 3% increased accuracy.

Balamurugan and Kannan have plotted graphs for different sampling technique vs accuracy for CART and C5.0 decision tree algorithms using Gini index and information gain respectively where authors have got higher accuracy for C5.0 [12]. Landsat-TM image and AVIRIS image have been used for classification; Bittencourt et al. has got average 92.9% correct classification by confusion matrix in [13].

From the literature survey it may be observed that object detection using thermal images is still an open problem and analysis is challenging. In this article, we have proposed a technique that analyses thermal images of various classified objects in a given environment and detect possible failure of the object due to increase in temperature and heat. The concepts used in this work include image analysis and feature extraction.

III. PROPOSED TECHNIQUE FOR ANOMALY DETECTION

The architecture for the proposed algorithm to monitor the heat emission of various classified (identified) objects (Power house, Switch, Switchboard, Transmission Center, Work station) for raising alerts and alarms due high heat or possible outbreak based on thermal images shown below in figure 3.1.

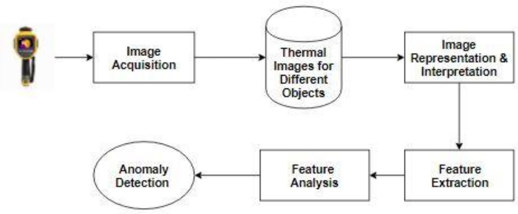

Fig. 3.1. Architecture diagram of proposed algorithm

Image acquisition is the first stage of any vision system which is hardware dependent. It is the formation of a digitally encoded representation of the visual characteristics of an object. Image acquisition is frequently believed to imply or comprise processing, compression, storage, printing and display of such images. Image acquisition could be in a digital form. This stage include preprocessing, such as scaling [14].

Image representation is a pixel data either the boundary of a region or all the points in the region. Image representation can be either external or internal. External representation is suitable when primary focus is on shape characteristic. Internal representation is suitable when the focus is on regional properties such as color and texture. In some applications, it is necessary to choose both representations [14].

Features are distinctive properties of input patterns. Transforming input data into the set of features is called as feature extraction. To decrease the amount of resources which is obliged to explain a large dataset can involve feature extraction. It is an attribute reduction process of collecting discriminative information from a set of samples. A latent semantic analysis, data compression and decomposition with projection, pattern recognition are some applications of feature extraction [14].

It is essential to examine features of various objects to ascertain the correlation between features and information about feature changes. Usually in conventional image processing, feature analysis is done manually which is slow, inefficient and prone to human error leads to dependable results. An automated feature extraction and analysis is important to many applications.

A. Image Acquisition

For preparing a dataset, thermal images are captured using fluke thermal camera with version Tis40. It's a fixed focus thermal camera with 160x120 resolution (19,200 pixels). From -20 °C to 350 °C (-4 °F to 662 °F) temperature measurement range can be offered by infrared camera with 3.5 inch, 320x240 LCD. From any smartphone, real-time communication by email is allowed with Fluke Connect with the storage of 4 GB internal memory with optional 4 GB micro SD card.

B. Image Representation and Interpretation

A detailed analysis has been done on all thermal images captured for each of the identified objects. This helped to identify the minimum and the maximum temperature with respect to temporal data for each object. For each of the different objects, temperature values vary with time. We have plotted time versus temperature values to get better idea of temperature variation for every objects.

C. Feature Extraction

Features are unique characteristics of images with numerous types which are generally classified into two types: structural and statistical features. The structure like as shape, loops, branch points, endpoints and dots can be represented by structural features. Statistical features are arithmetic measures of pixel intensities calculated over thermal images [15]. For the images captured using thermal camera, significant statistical features like temperature, area, mean, median, variance, skewness, kurtosis and RGB color value were computed which are used as the elements for feature analysis.

D. Feature Analysis

It is essential to learn features of various objects for establishing the correlation between features and information about feature changes. An automated analysis of the extracted features is necessary for performance evaluation of the obtained features. After extracting features from images, validation on test data with the ground truth is performed. For this process, manual annotation of time and object to code has been done which is used as the ground truth.

E. Anomaly Detection

For classification of test images and anomaly detection, decision tree approach is used. Due to the capabilities like assessing comparative significance of variables, handling of missing values, prediction and data manipulation; it is significant to choose decision tree.

Figure 3.2 shows the day versus temperature. For different objects, we have to compute minimum and maximum temperature value as well as threshold temperature value by taking average mean value. In the below figure 3.2, x-axis represents 5 days (Day i) and y-axis stands for temperature (T_i).

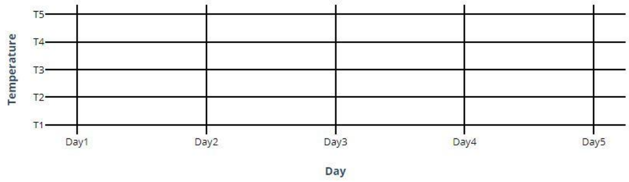

Fig. 3.2. Day versus Temperature graph

Table 3.1 describes objects O_1 to O_5 for different objects such as Power House, Switch, Switch Board, Transmission Center and Work Station. T_{ij} is a threshold value which is specified in degree Celsius. In our proposed work, we have used bimodal thresholding technique. The first threshold indicates the object emits very high heat which may result in possible fire breakout, which is termed as anomaly. The second threshold indicates the severity of the anomaly, where *i* indicates the object and *j* indicates whether it is first threshold or second threshold value.

Table 3.1. Threshold Temperature value for different Objects

Object	First Threshold Temperature	Second Threshold Temperature
O_1	T_{11}	T_{12}
O_2	T_{21}	T_{22}
O_3	T_{31}	T_{32}
O_4	T_{41}	T_{42}
O_5	T_{51}	T_{52}

For deciding first threshold temperature (T_{i1}) of object, we have taken average mean value from all temperature values for individual objects. The first threshold value T_{i1} is used to distinguish whether object has a chance of fire or non-fire. The second threshold value is decided based on first threshold value and maximum temperature value of each object. Every object has bimodal temperature threshold value T_{i2} for analyzing the anomaly.

In data mining for classification based on multiple covariates or for improving prediction algorithms for a target variable, Decision tree methodology is usually used. It is a non-parametric algorithm which efficiently deal with large dataset without impressive a complicated parametric structure. To build a decision tree model using the training dataset and a validation dataset to decide on the appropriate tree size is required to attain the optimal. To decide the class for test case, we have used decision tree method.

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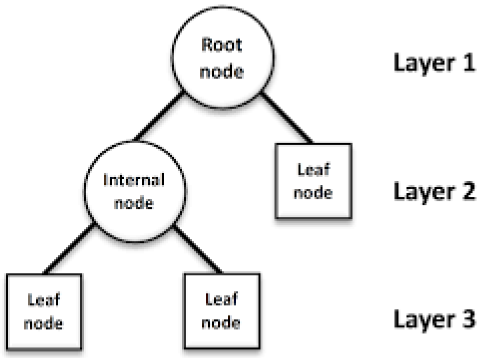

Fig. 3.3. Decision Tree with different layers

IV. EXPERIMENTAL RESULTS AND DISCUSSIONS

A. Dataset Description

The thermal images are collected for various objects which emit heat and radiation. Objects has an image which has array of temperature value in spatial domain. Figure 4.1 shows a list of objects used. Thermal images have been acquired by using FLUKE TiS40 thermal imager; images observed for an element of time which comprises of images of 5 objects at various time intervals e.g. starting from 9 AM to 3 PM. These images are captured at 5 sampling intervals in a day (after 1 hour interval) in a day; at the same time, this data acquisition process is continued for next 5 days. Likely, a total 125 thermal images of every object for various classes have been collected and used in this work for analysis.

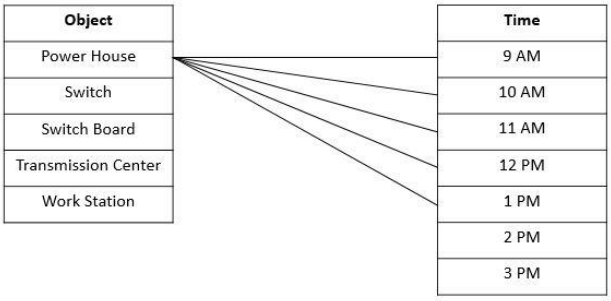

Fig. 4.1. List of objects and time of image acquisition

B. Image Representation and Interpretation

The graph in figure 4.2a to 4.2e shows the time vs temperature for various objects included for this study. For time interval of 11 AM, the temperature range is from 101 to 108. While for time interval of 12 PM, the temperature range is from 103 to 109. The temperature range has been increased

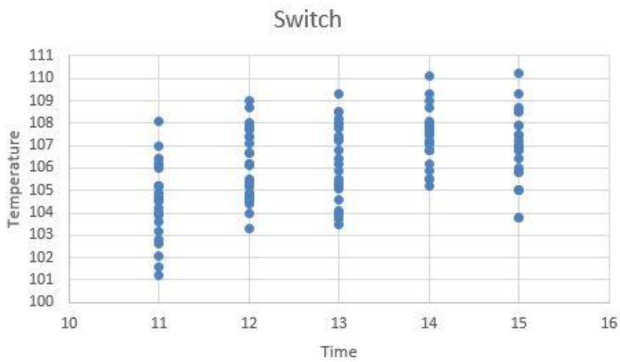

Fig. 4.2a. Time versus Temperature Graph for Switch

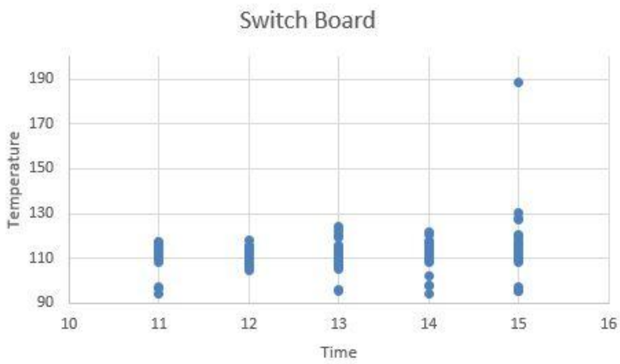

Fig. 4.2b. List Time versus Temperature Graph for Switch Board

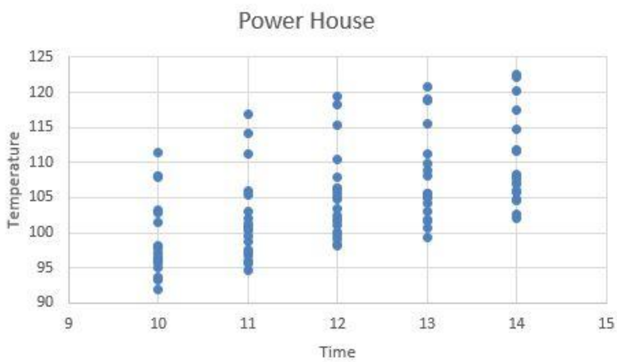

Fig. 4.2c. Time versus Temperature Graph for Power House

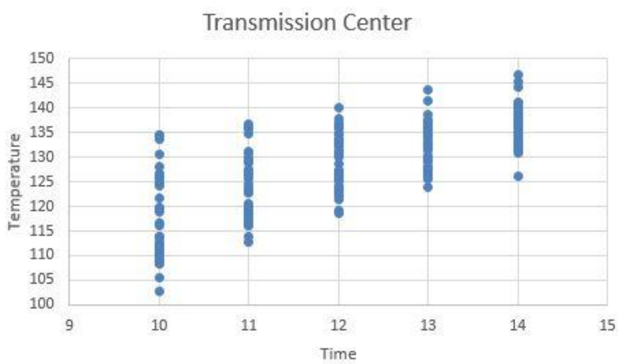

Fig. 4.2d. Time versus Temperature Graph for Transmission Center

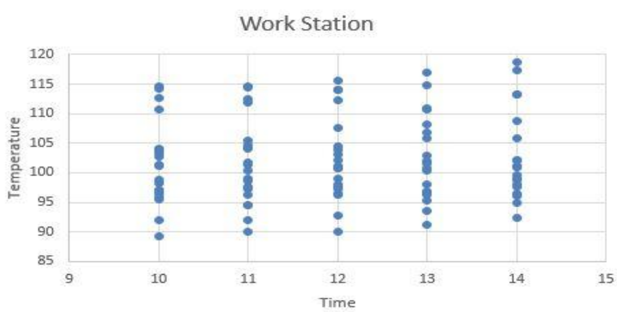

Fig. 4.2e. Time versus Temperature Graph for Work Station

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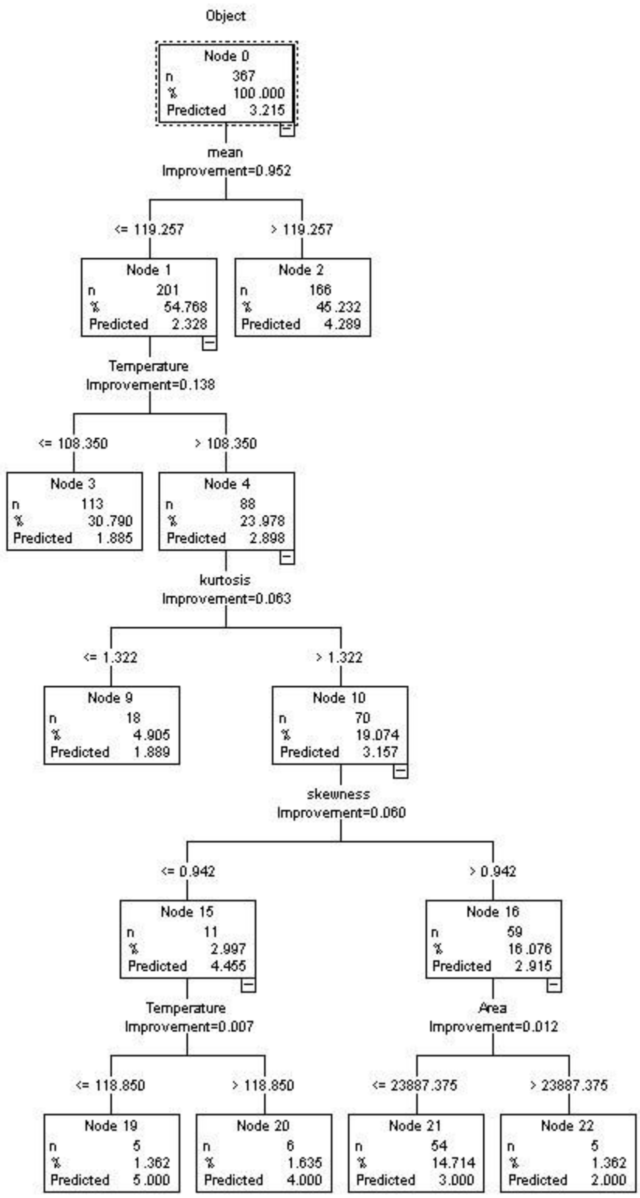

Fig. 4.3. Decision Tree using IBM SPSS Tool

by every sampling interval. The maximum and minimum temperature value have been found from the graph for every object and based on that, it has been concluded that first to get mean average value for deciding first threshold value (T_{i1}) and the mean average of first threshold value and maximum temperature value have been taken to find the second threshold value (T_{i2}) of that object. The anomaly has been found based on second threshold value (T_{i2}). The same procedure has been followed for every object by fixing the threshold and finding the anomalies. The temperature characteristic of the remaining objects are shown in figure 4.2a to 4.2e.

C. Decision Tree Classification

For the given data set which has 646 thermal images, a decision tree has been built using IBM SPSS toolbox [16]. Figure 4.3 shows the 5-level decision tree generated.

In figure 4.3, each node in decision tree contains frequency value (n) and predicted value. Based on the similar sample and homogeneous data, child node are presented from parent node. It may be observed that in each level, similarity between data is increasing.

To identify the actual object, DecisionTreeClassifier method has been used from sklearn [16] library for classification purpose. In Table 4.1, the metrics precision, recall, F1-score and support are calculated when entropy is not taken as one of the parameter for DecisionTreeClassifier method. It is observed from Table 4.1 that the first object class and the second object has same support value of 24 but are differing in precision, recall and F1 score metrics, the second object class has higher precision and recall value than 1st class object which implies that the second class object comprises of higher true positive values than first class object; whereas the minimum support value was observed for the third class object of value 21 with increased value of precision and recall along with F1 score of 1.00, 1.00, 1.00 respectively; the highest value of precision and recall was observed in the third class recording value of 1.00 which implies that third class is observed gaining higher accuracy than other classes; lower value of precision was observed on the class first having value of 0.56 and lower value of recall was observed on the fifth class having value of 0.68 which indicates that the data contains more insensitive information or more false positive values.

Table 4.1. Validation Measures

Objects	Precision	Recall	F1-Score	Support
1	0.56	0.75	0.64	24
2	0.77	0.83	0.80	24
3	1.00	1.00	1.00	21
4	1.00	0.94	0.97	33
5	0.95	0.68	0.79	28
Avg / Total	0.87	0.84	0.84	26

Table 4.2 and 4.3 shows True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN) for 5 different objects. Diagonal elements of Table 4.2 and 4.3 are True Positive (TP) value for the respective classes. With the accuracy 0.84 and without using parameter entropy, there are false negatives as well as true negative in Table 4.2. The misclassified samples are 21 in Table 4.2. The accuracy value is 0.84 for data in Table 4.2. If entropy is given as one of the parameters to Decision Tree Classifier method, then confusion matrix as shown in Table 4.3 shows an accuracy value 0.91. The number of misclassified samples are decreased with value 12. True Negative (TN) and False Positive (FP) decrease when entropy is a parameter, shows presence of higher random values.

Table 4.2. Confusion Matrix without giving entropy as a parameter to method

		Actual Objects				
		1	**2**	**3**	**4**	**5**
Predicted Objects	**1**	18	6	0	0	0
	2	4	20	0	0	0
	3	0	0	21	0	0
	4	1	0	0	31	1
	5	9	0	0	0	19

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Table 4.3. Confusion Matrix with entropy as a parameter to method

		Actual Objects				
		1	**2**	**3**	**4**	**5**
Predicted Objects	**1**	20	4	0	0	0
	2	0	21	0	0	3
	3	0	2	21	0	0
	4	1	0	0	32	0
	5	4	0	0	0	24

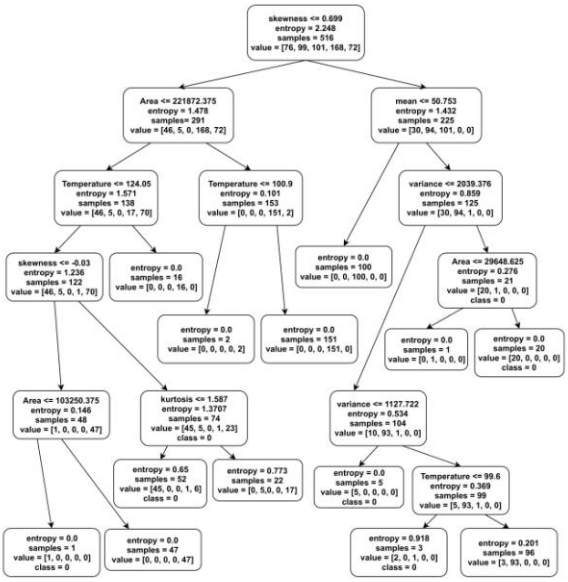

Fig. 4.4. Decision Tree including entropy as parameter

Accuracy increases when entropy is included to generate decision tree to DecisionTreeClassifier method. Highest value of entropy is observed as 2.248 which contains maximum number of samples 516. The decision tree shown in Figure 4.4 has 6 layers which are constructed that breaks the dataset down into smaller subset eventually resulting in a prediction. The root node partitions the data using the feature that provides the most information gain. The features are randomly permuted at each split. The value list shows how many samples at the given node fall into each category. Layer 2 contains two nodes which are created based on comparison of area and mean. Object class 4 and class 5 are separated based on temperature values which are lesser than 100.9 and lesser than 124.06 respectively. In layer 3, class 2 is separated based on variance value which is observed as 2039.376; whereas in layer 4, the same class 2 is separated with variance value 1127.722. All nodes of decision tree are separated based on feature values. Figure 4.4 is showing decision tree when entropy is taken as one of the parameters in DecisionTreeClassifier method.

Decision tree simplifies difficult relationships between input variables and target variables by splitting original input variables into considerable subgroups for easy understanding and interpretation. This algorithm is a non-parametric method without distributional suppositions. Decision tree algorithm handles missing values without needing to option to charge and intense skewed data without needing to do data transformation. This algorithm is healthy to outliers. Decision trees implicitly perform variable screening or feature selection. Nonlinear relationships between parameters do not affect decision tree performance [16].

Using Decision tree, it is possible to classify objects from thermal images. Based on the temperature value for a particular object, we can find minimum and maximum temperature of each object. Feature analysis helps to predict anomaly; raising alerts when the temperature exceeds a threshold value. This experimentation has shown that thermal image analysis is useful in anomaly detection such as possible outbreak of fire due to very high temperatures.

V. CONCLUSION

In this article, we have proposed a novel technique using thermal images to identify (or predict) possible outbreak of fire (or short circuit) of various objects (or assets which emits heat) in any given environment such as offices, hospitals etc. which is essential for disaster prevention and management. Decision tree has been used as a classifier to identify objects and using entropy as an important feature, anomaly detection has been performed. It is observed that thermal images can be used for anomaly detection. Further exclusive study on thermal images will be useful for many such critical application towards disaster management.

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