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Forest fire management using machine learning techniques

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ABSTRACT

As per the latest survey produced by the Forest Survey, the forest cover is 19.27% of the geographic area. According to this report every country can meet the human needs of 16% of the world's population from the 1% of the world's forest resource. The Forest Survey said that 90% of the forest fires created by humans. They pose a threat not only to the forest wealth but also this leads to the main threat to biodiversity, a change in the ecosystem. The environment gets dry and twinges, which leads to produce flames in the forest. There are two types of forest fire i) Surface Fire and ii) Crown Fire iii) Ground Fire. Surface Fire: The forest fire starts its flame primarily as a surface fire, spreading along the ground with the help of dry grasses and so on. Crown Fire: It starts flame on the crown of the shrubs, bushes and trees and sustained on the surface. This type of fire is very dangerous because resinous material given off burning logs burn furiously. If there is a slope with fire then the fire spread from the top of the slope to the down. Ground fire occurs in the humus and peaty layers beneath the litter of under composed portion of forest floor with intense heat but practically no flame. Such fires are relatively rare and have been recorded occasionally at high altitudes in Himalayan fir and spruce forests. In Remote sensing field, the knowledge of surface temperature plays a vital role. By using brightness and emissivity feature, temperature mapping and analysis can be done. The surface temperature values are measured to detect the forest fire from the ASTER image. ASTER stands for Advanced Space borne Thermal Emission and Reflection Radiometer. ASTER image contains 5 thermal bands (wave length ranges from 8.125 μm to 11.65 μm) and these are used in comparison. To convert digital numbers to exoatmospheric radiance, ASTER thermal bands are used. The converted exoatmospheric radiance is then mapped into surface radiance using the Emissivity Normalization method.

1. Introduction

In this technique, the emissivity of the Investigation area is assumed as constant. The surface temperature is finally extracted from the surface radiance. A comparison has been made between the extracted surface temperature values and the individual ASTER temperature bands. By applying the comparison, a positive correlation has been identified. The conversion related information like UCC and Earth-Sun Distance in Astronomical Units are published in ASTER user manual gains and offsets. Separability of fire spectral characteristics was used in onboard fuzzy logic approach to detect the forest fire spots in the Brazilian Amazon forest [1]. The synthetic Aperture Radar tutorial [2] contains the basic principles, theories and some techniques like polarimetry, interferometry and differential interferometry and the emerging techniques like polarimetric SAR interferometry, tomography and holographic tomography [3]. SAR tutorial gives the vision about the SAR remote sensing. The main complication is to detect forest fire using spectral characteristics like pixels and so on. To overcome this difficulty the pixels are taken under empirical characteristics [4]. An algorithm to identify the forest fire in AVHRR (Advanced Very High-Resolution Radiometer) series of satellites is proposed. Linear functions are used to represent the Decimal values in the satellite image. The decimal values are deviated

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due to spectral response, land surface resolution, the object size, etc. The pixel variation due to climatic and degradation of sensor can be recovered with the help of some error correction techniques in the decimal values. The extracted temperature values range from -50^{o} C which corresponds to the Decimal Number 0 and the values are increased by 0.1^{o} C per Decimal Value. This can be defined as shown in Eqn (1).

$$\text{Temperature in C} = (\text{count} \times 0.1) - 50 \tag{1}$$

The numbers of available bits are used to calculate the number of DN values in the infrared or the thermal image [5]. To analyses the thermal band about the forest fire the different set of images are collected at different times and different exposures which leads to radiometric correction in the required data. The algorithm needs consistent data at different weather conditions at various locations inside the forest.

As an outcome, the security of AI (Artificial Intelligence) turned into a center region for research as of late. Regardless of truly impressive advances in chosen regions identified with AI security, inadequacies were recognized on all encompassing methodologies that take a start to monitor on the dangers related to the designing of ML-based control frameworks and their certification. Applying an exemplary procedure of wellbeing designing, our paper gives a complete and methodological examination of the security perils that could be presented along the ML (Machine Learning) lifecycle and could think twice about safe activity of ML-based CPS. Recognized risks are outlined and clarified utilizing a true application situation—a self-ruling shop-floor transportation vehicle.

Digital actual frameworks are frameworks that constantly associate with the actual world and human administrators. Consolidating the digital and actual universes permits the development of innovations, which cultivates advancement for a wide scope of businesses. The Cyber-Physical Systems (CPS) people group has been encountering a solid push towards incorporating AI in their frameworks. Other than the huge measure of analyzable information, AI calculations help to dominate control issues that don't loan themselves to conventional algorithmic control draws near. CPS applications incorporate clinical gadgets and frameworks, helped living, traffic light and security, progressed car frameworks, flight and aeronautics programming, basic appropriated advanced mechanics, fabricating, among others, where the majority of these applications are security basic. Mechanical CPS-based applications have likewise been created and conveyed in Industry 4.0. Through CPS, Industry 4.0 (likewise alluded to as Smart Factory) is centered around making savvy items, systems and cycles [6]. In the Industry 4.0 setting, a legitimate safe joint effort between people what's more, machines is required, because of the inescapable use of Machine Learning (ML)-based robots (mechanical , administration , versatile robots, like Autonomous Intelligent Vehicles (AIV)) in plants [7–9]. These CPS join ML segments to perform complex undertakings like example and picture acknowledgment (i.e., errands hard to adequately perform utilizing algorithmic strategies alone) [10]. Alongside its developing applications, wellbeing parts of AI turned into an urgent subject of exploration [10,11]. For most true applications, the security of ML-based frameworks should be assessed and guaranteed.

2. Related works

The following rule is used to select the pixel from the satellite image. This technique is used to detect the forest fire by INPE which is purely based on the unsupervised clustering algorithm. If the area is Ocean then the pixel values can be removed. The threshold value can be fixed based on the information gathered on the forest area like the temperature and the fired area [19]. Sometimes data mining, histograms are used to gather the spectral characteristics about the satellite image [7]. Pasquale Imperator [13] suggested detecting forest fire by using Sentinel-1 C-band synthetic aperture radar to find the fire scars. To identify the fire scar, fuzzy algorithm is used with different set of images. The area taken to detect the fire was Sardinia Island during summer season. There are 4 basic scattering terms are identified [13,14]. They are: Layer volume scattering, Surface Volume Interaction, Top Surface scattering and Bottom Surface scattering. Radiative transfer methodology uses the scattering scheme to detect the forest fire area [1,9,10,18]. In paper [22] Land surface temperature is measured. The collected homogeneous area images are analyzed under atmospheric corrections. Field emissivity technique is used to detect the forest fire. To retrieve the LST values the following steps to be carried out to perform atmospheric corrections:

The value is given by the technique ACT. The LST value differs in ACT and radiosonde profiles due to the changes in the atmospheric values and the water vapor profiles. The Land Surface Temperature is measured with the help of the following features.

Top of Atmosphere temperature
Land Surface Emissivity
Channel Brightness temperature
Atmospheric water vapor
Effective wavelength

Especially in recent years, the scale of enrolment in our country has continued to expand, and the level of running schools has been becoming increasingly diversified. The reform of logistics socialization in ML component has been deepened, and exchanges societies are becoming more frequent. The campus is densely populated and complex. The group activities are very frequent. Once a fire occurs, it can easily cause heavy casualties. The damage will be immeasurable and it will form a nasty social impact [1]. Therefore, the problem of fire safety management in ML component has become one of the hot issues of scholars at home and abroad. Scholars have carried out research mainly around the fire safety management system in ML component [2], fire safety problems in ML component [3], and countermeasures for fire safety management in ML component [4]. These factors and countermeasures are mainly some concrete solutions, and the economic problems such as safety input and output have not been considered at present.

Considering our model utilization of a self-driving vehicle in a manufacturing plant, the Requirements stage can present a few risks as referenced previously. At the absolute starting point, when characterizing the dataset models, we ought to consider under which conditions oneself driving vehicle will work (e.g., measure of light, recognizable proof of which objects/obstructions it ought to identify). In the event that this definition isn't performed satisfactorily, this could bring about an inadequate meaning of information. For instance, if the measure of light in the room is not exactly a few lumens worth, and this situation was not characterized in the necessities, the vehicle could miss the identification of an article and cause hurt. Then again, a mistaken target work definition may happen for the situation where the significance of identifying certain obstructions it isn't adjusted effectively [5] (e.g., the mistake of not distinguishing an individual ought to have a higher load than the instance of not recognizing a case).

A lacking exhibition measure chosen that could likewise affect the activity of oneself driving vehicle. For instance, a framework that should identify people and different obstructions, neglects to characterize human presence, bringing about a FN case and at last in colliding with an individual. Then again, in a FP case (i.e., bogus alert), such a ML-based recognition framework might result in consequently applying the brakes of the vehicle to forestall colliding with what the calculation distinguishes as a hindrance. Limiting FN appears to have more weight than limiting FP, in light of the fact that in this situation FP could be considered to have just an impact on functional execution. In any case, such FP could additionally cause a wellbeing basic risk if the vehicle stops for no essential explanation. Hence, existing measures should be painstakingly upgraded to fit the requirements for assessing a protected exhibition of ML models [6]. The deficiency of approval/confirmation prerequisites likewise addresses a wellbeing danger in the production line setting when the meaning of some worth is wrong or inadequate. Characterizing a non-adequate runtime execution can later convert into hitting an impediment, if for instance, a hindrance was identified inside the worth characterized; notwithstanding, since the definition was wrong, it actually caused a mishap. Finally, in self-ruling vehicles the expression "safe state" alludes to a state where the danger from the framework is sensible. In any case, when utilizing the term safe express, the test depends on the distinguishing proof of an edge, that is, an insufficient safe working worth under which the danger level isn't satisfactory. Subsequently, the meaning of this worth could likewise bring about a mishap in the manufacturing plant.

2.1. Information management

The Data Management stage is liable for obtaining significant information for the machine learning model to have the option to make forecasts on future information. The contributions of this stage are the arrangement of necessities that the application needs to accomplish, and the yields are made by the preparation and test datasets, to fill in as contributions for the Model Development and Model Testing and Verification stages, individually. For creating such datasets, this stage centers around four unique exercises: information assortment, information comment, information preprocessing, and information increase [7–9].

Reasonable safety input is an effective way to reduce the occurrence of safety accidents [10]. However, higher education institutions which are dominated by teaching and research should not step up their input step by step. While considering the safety investment, they must further consider the benefits and objectively evaluate the efficiency of fire safety management, so as to find the problems existing in the fire safety management of universities. They should also rationally allocate resources, optimize management programs, and improve management efficiency. On the basis of referring to relevant literature, the input and output index system of fire safety management in colleges and universities is constructed in this research. Data envelopment analysis (DEA) is used to evaluate the efficiency of fire safety management in universities, so as to provide reference for universities to improve the management level of fire safety. At the same time, it is expected to provide new ideas and methods for the objective measurement of the efficiency of fire safety management in universities.

2.2. Security and machine learning

AI calculations are progressively utilized in frameworks that include people or work in imparted conditions to people, bringing about developing consideration regarding the parts of the wellbeing of those frameworks over the most recent couple of years. To give a superior comprehension of the terms and documentation of wellbeing and AI handle, this segment presents explanations for the two regions separately, and afterward for the crossing point of both. For that reason, the following subsections will zero in on the meaning of a couple of measurable AI documentations, just as on the relationship of those documentations with wellbeing ideas. Toward the finish of this segment, security in AI is additionally delineated by introducing a model use of a wellbeing basic CPS where a ML model is coordinated. Across different designing disciplines, security is an oftentimes utilized term, which assigns the shortfall of disastrous results on the user(s) and on the climate.

3. Methodology

3.1. Input indexes of fire safety management in ML component

The input in fire safety management in ML component includes pre input and control input [6]. The so-called pre input is the planned and predictable inputs of manpower, material and financial resources in advance to prevent the occurrence of fire and make timely and effective for fire-fighting after the fire. Control inputs are human, material, and financial resources to control minimum casualties and property losses after a fire.

The input of fire safety management in universities is divided into two aspects: safety control input and safety technology input. Fire safety control inputs include fire safety engineering and facilities operating costs, the cost of safety testing equipment, the hiring of fire safety managers, the cost of staff safety education, training and so on. Fire safety technology inputs include fire safety equipment costs, the inspection cost of fire hazards equipment, and the introduction cost of fire technology. In this paper, the total cost of fire safety management in colleges and universities (non-cost input is converted into cost input) is taken as input indicator of fire safety management in colleges and universities [10].

3.2. Output indexes of fire safety management in ML component

The evaluation of fire safety management in universities is a complex systematic project, involving many quantitative and qualitative indexes. With referring to the existing literature [7], in the light of scientific, objective, independent, systematic and measurable principles, the performance evaluation index system of fire safety management in universities is established, as shown in Table 1.

3.3. Evaluation model of fire safety management efficiency in ML component based on DEA

Data Envelopment Analysis (DEA) was first introduced by professor Charnes, Cooper and Rhodes, famous research experts at the University of Texas in the United States [8]. It is mainly used to evaluate the relative validity of complex systems with multiple inputs and outputs. In DEA, the object studied is called the DMU Making Units (DMU), which has certain inputs and outputs. And in the process of converting input into output, it tries to achieve the structural unit of its own decision objectives [9].

The basic idea of DEA is that a dynamic system is regarded as a process in which a certain amount of "factor of production" is produced within a certain range and a certain amount of "labor achievement" is produced. Through the comprehensive analysis of input and output data, the quantitative indexes are obtained to evaluate the comprehensive efficiency of each DMU, so as to determine whether each DMU is DEA effective. On the other hand, the DEA method uses mathematical programming to project each DMU onto the effective frontier. The relative validity is evaluated by comparing their degrees of departure from the leading edge.

Based on the analysis of the decision-making units and input and output indicators, the total cost of fire safety management in universities is used as input indicators of the DEA model. All indicators of fire safety management performance evaluation index system in the second part are used as the output indicators of DEA model. The DEA model is set up as shown in Table 2. After substituting data, whether one or several universities' fire safety management is effective relative to other enterprises can be evaluated.

4. Proposed method

The image is preprocessed using Visual assessment of image co-registration, Radiometric Calibration, Cloud and Cloud Shadow Masking, Haze Correction and Radiometric Normalization. The preprocessing step removes the irrelevant data (i.e. the data which are not necessary to predict the temperature) and the errors (due to climatic change and the satellite problems) present in the collected image. The below flow chart Fig. 1 shows the structure of the proposed method [12].

The Landsat Thematic mapper images are corrected to Universal Transverse Mercator projection with 30 m spatial resolution and it reduces the root mean square error. To match the slave image, linear shift is required with some set of images which are taken as master [13–17].

Table 1
Performance evaluation index system of fire safety management in ML component.

First-level index	Second-level index	Third-level index	Index description
	Fire supervision B_1	Fire hazard rectification rate C_1	The ratio of the number of hidden fire hazards and the number of hidden fire hazards should be measured to reflect the responsibilities of in ML component in dealing with fire hazards.
		Fire administrative penalty rate C_2	The ratio of the number of administrative penalties to the number of illegal acts found should be determined.
		Fire accident disposal rate C_3	The ratio of the number of fire accidents to the number of fire accidents should be measured to reflect the work of the universities on fire accidents.
		Safety management standardization level C_4	Is the fire department responsible for the fire safety management according to the functions and procedures prescribed by law?
	Fire rescue B_2	Fire rescue success rate C_5	The ratio of the number of successful fire fighting fires and the total number of participating fire-fighting teams in universities is measured.
Fire job performance		Emergency rescue rate C_6	It refers to the situation that universities have successfully eliminated the risk source of the accident or successfully rescued the trapped personnel and responded to the emergency rescue duty of the university.
	Public service B_3	Satisfaction of teachers and students in Fire Department C_7	This indicator is a subjective indicator, which can be obtained by sampling.
		Safety awareness of teachers and students C_8	It reflects the effectiveness of fire publicity, education and safety training, and the data can be obtained by sampling.
		Knowledge rate of fire protection between teachers and students C_9	It refers to the degree of mastery of fire safety knowledge among teachers and students, and the data can be obtained by sampling survey.
		University fire safety level C_{10}	It refers to the degree of fire safety in universities, which can be scored by expert evaluation.
	Fire safety status B_4	Fire rate C_{11}	Negative index, it refers to the rate of fire per 10000 people in universities.
		Fire casualty rate C_{12}	Negative indicators, which refers to the rate of fire casualties per 10000 people in ML component.
		Direct economic loss of fire C_{13}	Negative indicators, it refers to the direct economic losses caused by fire in universities.

Table 2
DEA model of efficiency evaluation of fire safety management in ML component.

ML component A	ML component B	ML component C	ML component D	Weight
^{x}1A	^{x}1B	^{x}1C	^{x}1D	Total fire safety charges u_1
^{y}1A	^{y}1B	^{y}1c	^{y}1D	Fire hazard rectification rate v_1
^{y}2A	^{y}2B	^{y}2c	^{y}2D	Fire administrative penalty rate v_2
^{y}3A	^{y}3B	^{y}3c	^{y}3D	Fire accident disposal rate v_3
^{y}4A	^{y}4B	^{y}4c	^{y}4D	Safety management standardization level v_4
^{y}5A	^{y}5B	^{y}5c	^{y}5D	Fire rescue success rate v_5
^{y}6A	^{y}6B	^{y}6c	^{y}6D	Emergency rescue rate v_6
^{y}7A	^{y}7B	^{y}7c	^{y}7D	Satisfaction of teachers and students in fire department v_7
^{y}8A	^{y}8B	^{y}8c	^{y}8D	Safety awareness of teachers and students v_8
^{y}9A	^{y}9B	^{y}9c	^{y}9D	Knowledge rate of fire protection between teachers and students v_9
^{y}10A	^{y}10B	^{y}10c	^{y}10D	ML component fire safety level v_{10}
^{y}11A	^{y}11B	^{y}11c	^{y}11D	Fire rate v_{11}
^{y}12A	^{y}12B	^{y}12c	^{y}12D	Fire casualty rate v_{12}
^{y}13A	^{y}13B	^{y}13c	^{y}13D	Direct economic loss of fire v_{13}

Note: Xij is the input variable; Y_{rj} is the output variable.

Then some original data are extracted from the raw set of data.

There are 2 steps are needed to mask the clouds and the cloud shadows. Cloud and cloud shadow pixels were detected based on rule based preliminary mapping from the calibrated image at first step [18]. This mapping was performed based on prior knowledge about the spectral environment. Each and every pixel in the image is classified under Snow Spectral Category and Cloud Spectral Category. Then the second step is clearing the cloud and cloud shadow pixels based on the topological and morphological methods. It removes the cloud and the shadows which are visually identified.

4.1. Radiometric Normalization

There are so many techniques used to remove the noise from the dataset. Varying atmospheric conditions are removed by using Complex radiative Transfer models [19]. This method measures the atmospheric optical properties to produce the improved reflectance values at the time of image acquisition. In DOS method [20] (Dark Object Subtraction). This method assumes the presence of dark objects with reflectance as nearly zero at all bands. The calculated average value to the effect of atmospheric condition was subtracted from all the pixels. Every collected Landsat image contains set of bands and each thermal band contains a set of decimal numbers for each pixel. Each decimal number should be mapped into a spectral radiance by the formula defined in equation (1). UCC_j is the Unit Conversion Coefficient (W $m^{-2}sr^{-1}$ μm^{-1}) taken from downloaded tar file. Calculate the TOA radiance from the spectral radiance using the following formula defined in equation 2. $E_{SUN,\lambda}$ value is extracted from the tar file, angle θ, wave length λ are also extracted from the satellite database and the distance between sun and earth value d is gained. The land area and the prediction area are to be identified. The pixel values which are more than 300 are taken as Prediction area.

5. Experimental results

In this section the experimental results are discussed and the performances are evaluated. The proposed method is applied to various set of Landsat images and Random Forest Technique is used for prediction. The Land area and the prediction area should be differentiated from the band after calculating the temperature (Land Areas-Red, Prediction Area-Yellow). Then the prediction areas in which temperature is greater than 300 K are differentiated by Yellow and the unused areas as Black after calculating the temperature values. Some set of images the intensity values are calculated for each pixel [21]. The set of intensity values are used to train the dataset whether forest fire is found or not. Finally, the highest intensity values should be calculated for that band.

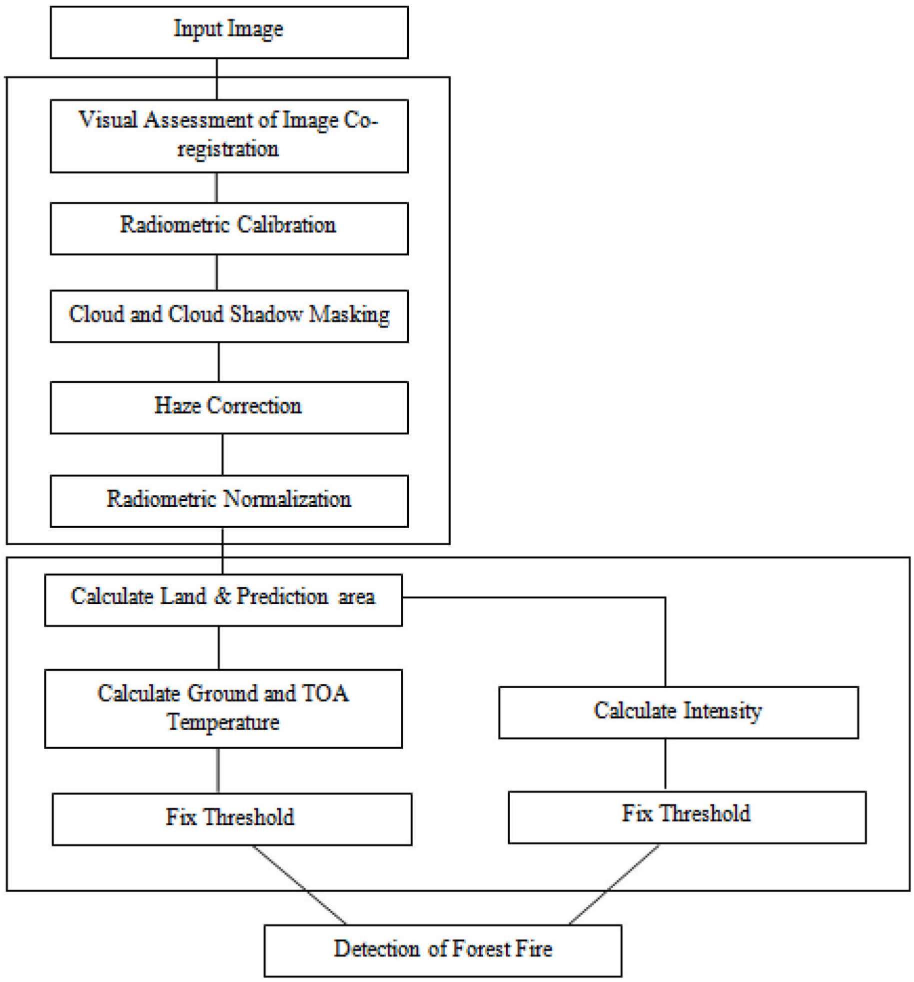

Fig. 1. Flow chart of proposed work.

The threshold for fire based on intensity is more than 150. Fuzzy classification is the process of grouping elements into a fuzzy set whose membership function is defined by the truth value of a fuzzy propositional function. Based on the Ground, TOA temperature and the intensity values the Forest sets are classified using fuzzy classification [22].

The Forest Fire and the normal images are considered to find the temperature in the specified area. The datasets are collected from the website www.usgs.gov. Forest area was taken to predict the forest fire. The datasets are collected before and after forest fire [23]. This proposed technique was used to detect the forest fire using the temperature (TOA and Ground) and intensity values. The unused areas are identified and the remaining areas are taken to predict the forest fire. T1, T2, T3, T8 are the bands used to predict the forest fire as shown in Table 3.

Table 3
Landsat Thermal Band Temperature and intensity values.

Band	Land area count	Prediction area count	Ground Temperature K	TOA Temperature K	Fire intensity
T1	331697	22438	140.6045	110.1442	117.3225
T2	325595	30408	310.8436	321.0228	172.7429
T3	288029	59186	252.7034	249.439	124.6941
T4	292028	56358	166.7463	169.9417	141.8019
T5	148587	41275	329.674	326.642	185.8025
T6	316530	38693	247.362	247.362	137.1461
T7	376029	36002	357.1242	357.1242	195.1356
T8	389689	36045	331.6986	331.6888	231.8506

Fig. 2 shows the analysis about TOA and Ground Temperature. The images are collected from Landsat-7 and Landsat-8 sensors. The Fire areas are calculated based on the intensity values of the pixels. Greater intensity values are used to calculate the temperature in the area. The values are projected in the Table 3. UCC values [24–26] are used to calculate the intensity values in the area. The threshold values are fixed based on the temperatures calculated from the bands. The highest temperature is found as 300 K. Thus, the forest fire is predicted if the temperature is greater than 300K.

6. Conclusion

In this study, DEA method was used to present a method for the quantitative evaluation of the efficiency of fire safety management in universities. The effectiveness of fire safety management in universities was tested through the comparison of a university and others. This kind of comparative evaluation is more objective and fair than that of a university alone. The dimension of the indexes in the model can be different. Different metrics have no effect on the results of the DEA model. The fire safety management efficiency of different evaluation units was evaluated. The implementation of the corresponding incentive and restraint measures can effectively improve the initiative of the safety management and control of the education director. The results of this study demonstrate that the proposed method to detect the forest fire and this technique is accurate. This suggested technique may be helpful to improve the detection process of forest fire. This evaluation shows the effective usage of remote sensing dataset for temperature mapping and prediction of forest fires. The features are identified to analyse the forest

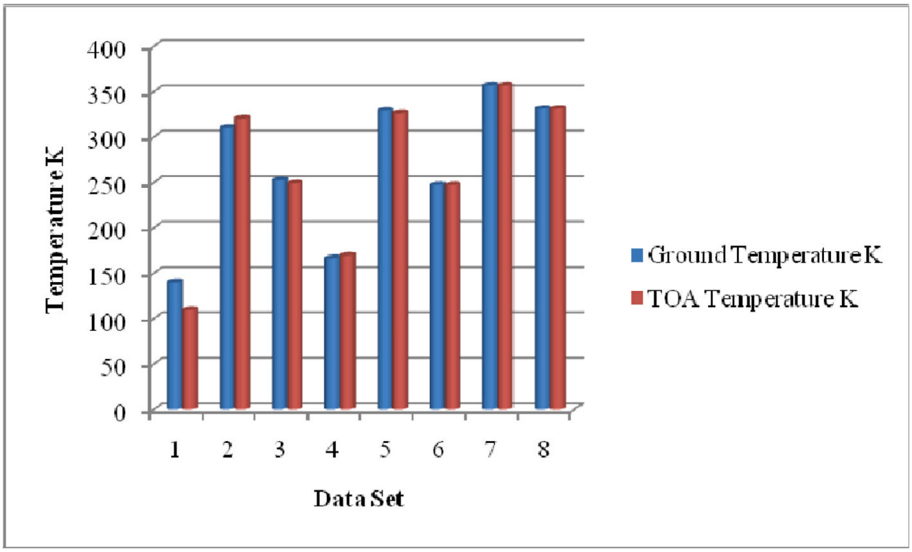

Fig. 2. Temperature analysis.

fire using the Intensity, TOA Temperature and Ground Temperature. Using the above parameters, the forest fire state is predicted and analyzed.

CRediT authorship contribution statement

Harishchander Anandaram: Conceptualization, Overall, Supervision. **Nagalakshmi M:** Data Collection. **Ricardo Fernando Cosio Borda:** Implementation, Validation. **Kiruthika K:** Methodology. **Yogadinesh S:** Additional Data Collection.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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