Auto digitization of aerial images to map generation from UAV feed

Raju Jagadeesh Kannan[1], Karunesh Pratap Yadav[2], Balasubramanian Sreedevi[3], Jehan Chelliah[4], Surulivelu Muthumarilakshmi[5], Jeyaprakash Jeyapriya[6], Subbiah Murugan[7]
[1]Faculty of Engineering and Technology, SRM Institute of Science and Technology, Tiruchirappalli, India
[2]MATS University, Arang, Chhattisgarh, India
[3]Department of Computer Science and Engineering, Sri Sairam Institute of Technology, Chennai, India
[4]Department of Computer Science and Engineering, Vel Tech MultiTech Dr. Rangarajan Dr. Sagunthala Engineering College, Chennai, India
[5]Department of Computer Science and Engineering, Chennai Institute of Technology, Kundrathur, Chennai, India
[6]ML Engineer, Apcomart Private Limited, Bangalore, India
[7]Department of Biomedical Engineering, Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, Saveetha University, Chennai, India

Article Info

Article history:

Received Dec 14, 2023
Revised Aug 2, 2024
Accepted Jul 5, 2024

Keywords:

Autonomous vehicles
Digitization
Index terms
Learning system
Unmanned aerial vehicles

ABSTRACT

Nowadays the rapid growth of unmanned aerial vehicles (UAVs) bridges the space between worldly and airborne photogrammetry as well as allow flexible acquisition of great solution images. In the case of natural disasters such as floods, tsunamis, earthquakes, and cyclones, their effects are most often felt in the micro-spaces and urban environments. Therefore, rescuers have to go around to get to the victims. This paper presents an auto digitization of aerial images to map generation from UAV feed at night time. In case of a power outage and an absence of alternative light sources, rescue operations are also slowed due to the darkness caused by the lack of electricity and the inability to light additional sources. In other words, to save lives, we need to know about all essential large-scale feature spaces in the dark so that we can use this information in times of disaster. The research proposed a soft framework for crisis mapping to aid in mapping the state of the aerial landscape in disaster-stricken areas, allowing strategic rescue operations to be more effectively planned.

Corresponding Author:

Raju Jagadeesh Kannan
Faculty of Engineering and Technology, SRM Institute of Science and Technology
Tiruchirappalli, Tamil Nadu, India
Email: jagadeeshkannan.r@vit.ac.in

1. INTRODUCTION

One important use of drone-based picture data acquisition and translation is nighttime mapping. It is broadlyutilized as an inherent portion of armed forces surveillance and edge security [1]. This model is typically distributed for automatic object identification and scene segmentation to realize a specified scene best and to alleviate connection with mapped features toaltering auto-target categorization [2]. The steps involved in object identification, classification, and scene segmentation are crucial for developing an integrated monitoring [3] and mapping system based on drones and swams [4]. Principal component analysis (PCA) [5], linear discriminant analysis (LDA) [6], and non-negative matrix factorization (NMF) [7] are among the major methods that are supported in this sector.

These methods are widely used and often provide a useful function for the process of automated feature extraction [8]. Next, K-nearest neighbor (KNN) or support vector machines (SVM) are used for locating and classifying points of interest using thermal or RGB surveillance data [9]. This methodoperates best in daylight images with adequate light. This paper describes a novel method for object mapping through drone use in low-light conditions. In this instance, we utilize RGB and thermal images [10]. Given the visual constraints imposed by the object, object detection on drone-mounted images is extremely sensitive to viewing angles. The classifier/mapper created for a particular viewing angle will not be able to recognize objects in other angles if the object is not symmetric [11]. As such, this lays the foundation for our work, leading to a better solution in the given scenario, assisting rescue workers in disaster zones, and increasing border security. The paper comprises modules, an auto-neural architecture generator, and a process that unites them [12]. First, thermal data of the victim's position is combined with data about the terrain, which has been colored in the dark. Then a fused 2 dimensional (D) topological model is used to depict the blockade, flooded, and debris locations, as well as night vision images that have been colorized [13]. With thermal vision, geographic geo-technologies can help people make decisions with enhanced rescue strategies. Accordingly, using a drone-based night mapping method is helpful for rapid response teams [14].

A multi-modal image fusion system that protects important information from the sender pictures by decomposing the input images using discrete wavelet transform (DWT) at four levels and NSCT at two levels. This technique shows a significant improvement in pixel clarity and maintains data at the fused image's corners and edges without any loss [15]. A machine vision application utilizing an image processing method established a new way of rice seed classification, which applies hashing techniques pre-processing of image prediction [16]. Linear regression algorithm, which calculates the value of a dependent variable, establishes an independent variable [17]. The scope is to expand an internet of things (IoT) system that assists sustainability and energy efficiency by providing real-time observing and insights into power utilization [18]. The benefits of incorporating IoT and geographic information systems in agriculture, with particular accent on the possible to transform soil observing and nutrients management to raise crop output while minimizing negative environmental affects [19]. Only contemporary image and signal processing approaches may reveal crucial insights into electroencephalogram (EEG) data. Image processing techniques meticulously analyze EEG images to reveal undetectable patterns. Advanced temporal and frequency domain signal processing may detect seizure precursors [20]. It easier to deal details and assets creating more cohesive ecosystem [21]. Increased connectivity and productivity in the cloud are both benefits of interoperability. It expands our knowledge of epilepsy and foreshadows a humane medical technology. Cloud computing, image processing, and signal processing enable us to understand seizures at a basic level rather than merely predict them. The results of this investigation are significant for creating personalized epilepsy treatment programs [22]. The data is stored, analyzed, and shown using Thing Speak, a cloud-based IoT platform. It has a simple interface which can be utilized to observe water levels, observe data from the past, and expand discovering which can be applied to handle water resources better [23]. Power quality observing in PV grid systems, this research offers an inventive strategy applying IoT [24]. The scope is to extend an IoT system that helps sustainability and energy efficiency [25].

2. METHOD

Data processing and product are both sections of the methodology, known as flight planning and data acquisition. In the flight planning and data acquisition' phase, efficiency is of the utmost importance because researchers must gather and collate infrared images of the study area. Proper flight planning is done once the requirements are investigated. Then the flight trajectory is calculated, and other variables like maximum flight time are defined to perform a smooth autonomous flight. A self-flying flight gathers infrared imagery from overlapping study areas. To ensure accurate data collection, these images have been organized and filtered. The first step, "data processing and data product," is to convert the infrared images into RGB bands using the IR-RGB image transformation. For a specific study area, several colored RGB images are mosaiced together to create an RGB mosaic. Additionally, IR images are used to process selected areas into IR mosaics. As a result, a subsequent mosaic is used to cover the area required. A new IR-RGB image fusion script is now available for download, allowing you to combine the fused image with IR and RGB features. Using the fused image, it is possible to use thermal and optical remote sensing techniques to map the victim's location. This, as shown in Figure 1, utilizes an auto neural architecture generator to process night time terrain mapping information, along with thermal imagery, to assist in locating victims in a natural disaster. The following night vision colorization algorithms have been found.

This paper's NCCA auto neural architecture algorithm presentation includes the network coded feature set. This correspondence allows us to learn how to render accurate edge maps, geometry, and colour while improving our accuracy. Work in low-light conditions because of using a network of feature maps. This means it is possible to identify missing features and complete the gaps in missing data segments, so you can get work done in these considerations. To build a network of coded feature sets, the scene and object features are grouped and labelled in order to create sets of feature vectors with different lighting conditions. The algorithm of network coded feature set is explained in [26].

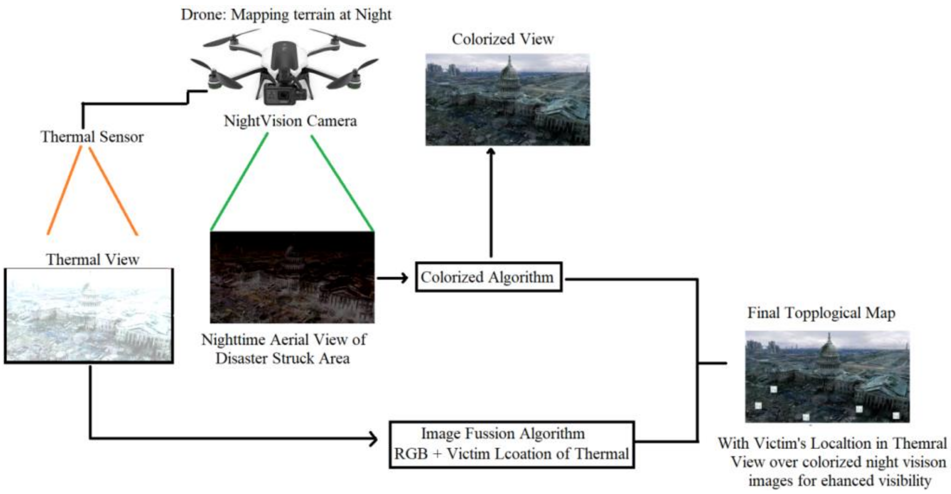


Figure 1. Illustration of night time mapping in tragedy strike regions to improve visibleness and localization of victims utilizing thermal image fusion

You can use an image format (a parameter index) that maps each training image to the right concentration of light field, color values, and light intensity. Refer to Figure 1 for clarification. When viewing objects from different angles, orientations, and lighting conditions, you should use the Tubule Net artificial intelligence (AI) module I to classify the objects. To organize images, you must use edge masks, the distribution of the objects in the image, and color. You should train your programmer to differentiate between up and down-sampled images to enhance object recognition. The process then continues by transferring to the Tubule Net module II, which will conduct light field association training using the previously classified output and the segmented edge mask derived from it. Intensity and luminescence in the scene understanding, Tubule Net-based feature pooling module III is used to identify what is present in the scene and search for objects within it (hyperparameters). Ensure that the colorization is correct by trying several times. It is necessary to train module IV of the Tubule Net, which was developed following steps 1 and 2. Results from module III can be used to compare module IV to module III. Module III should be retrained after it has been fed errors and complicated masks so that the error value converges to its maximum. Convergence and perceptual validation effectively promote only the most relevant results. Once the noise values have been fed into the check, the program uses this information to suggest improvements to the sound. Each pixel learns the overall color distribution by looking at the entire image. TubuleNet was developed using Tubule-based neurons, which learned not the whole but only the specific times to fire information to activate interconnected components or for applications such as game theory.

The “Tubule” is a word used to describe a set of neural networks grouped in impressive numbers and found close (2). Category theory and formal grammar are both involved in activating the Tubules. To transmit weighted information, a Tubule in the network must be activated. At the beginning of the experiment, the activation threshold is set to one. The conventional deep learning network represented by number 1 is identical to the rectified linear unit (ReLU) activation function with input and output convolutional layers, which is a ReLU activation function. The network created by Tubules’ tubular structure is “hidden.” Tubule Net (2) connects to the line sequencing pool whenever the activation function in that Tubule Net (2) is activated. When the last odd activator in the Tubule Net’s modules is activated, the Tubule Net is then part of the network. The threshold value now functions based on the various input values from the modules. Because this procedure stores values in memory, the connection is optimized. Changing the order of inputs used in the calculation gives a wide range of responses for inputs with similar characteristics. Green-tinted night vision is used to interpret and visualize images.

First, perform the following actions: when doing batch image analysis, you will need to extract the color and light intensity values for each batch of images and then save these values as an index of parameters for each training image. Thanks to the Tubule Net AI module I, I can be used to classify a wide range of objects and view them from various angles, orientations, and light fields, thanks to the Tubule Net AI module

I. Classifying an object is by applying an edge mask and a color distribution. You should also train your program to differentiate between up sampled and down sampled images to enhance object recognition. Allow the module to learn about object-to-associated light field association concerning the color distribution for each pixel and connect the module's findings to the Tubule Net module II, which has been given the parameter index derived from step 1. Please execute the Tubule Net-based feature pooling module III. Until you are satisfied with the colorization result, keep repeating the loop.

By the results of steps 1 and 2, Tubule Net module IV should be developed. Results from module III can be used to compare module IV to module III. Module III should be retrained after it has been fed errors and complicated masks so that the error value converges to its maximum. After convergence and perceptual validation have been completed, the best-suited results should be pushed forward. Activation of each Tubule results in the transmission of information between Tubules close to one another, as shown in Figure 2. Checking for correctness and improving the behavior follows the later values. If we were to boil it down to its essence, it's determining the color distribution of each pixel.

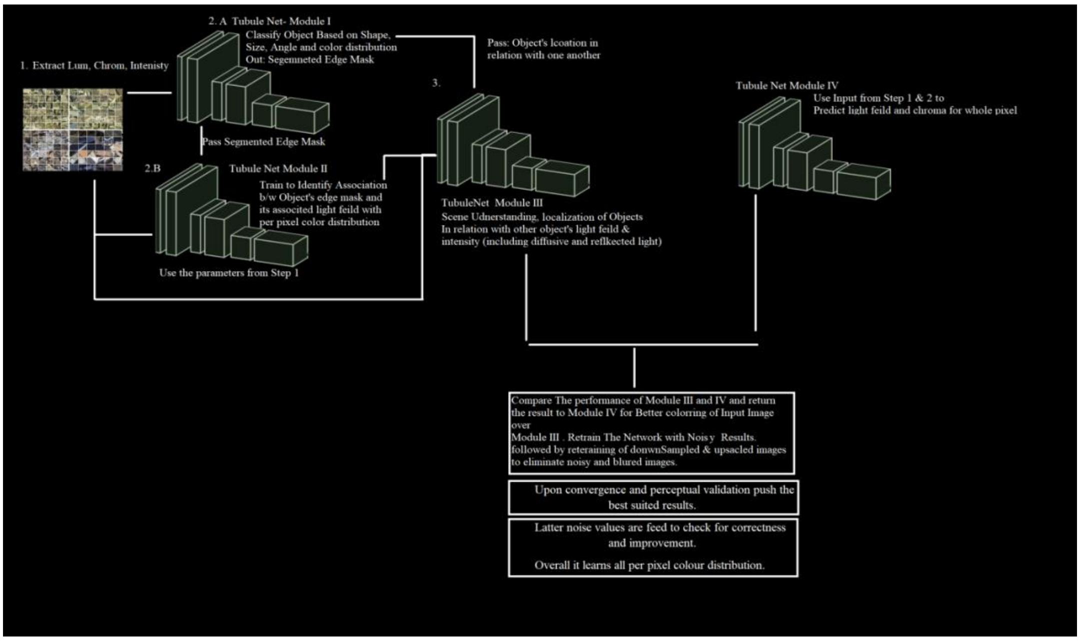


Figure 2. Diagram of sub-modules in Tubule Net

Although Tubule Net is established on Tubule-based neurons that learn the system's complete mechanics, rather than simply learning a portion of it, the system can only fire data in a particular pattern to activate interconnected components or neural sets similar to those already activated. Ideally, the neural networks should be arranged so that there are an odd number of neural networks in a given set; the result should be one Tubule or group of neural networks. For every Tubule in the system, an activation function is developed in the form of a factor based on category theory. During the early stages of development, there is a uniform activation threshold. Input and output procedures are described in detail. They are deep learning networks in the conventional sense, but instead of using the ReLU activation function, they use the convolutional layer (CONV) activation function. The hidden network is formed by the nonstructural network that exists within Tubules. A connection is established to the next Tubule Net in the pool each time the activation function of a Tubule Net in a line sequencing pool is activated. The data is shared when the last odd activator in a Tubule Net is activated, as shown in Figure 3.

It depends on the type of input values that are used in the module for each module. Significant optimization of the connection can be attained by storing values in memory. Changing the order of inputs used in the calculation gives a wide range of responses for inputs with similar characteristics. An extensive set of Bayesian features (such as the classification of nodes established on the compliance theme, as well as positive or negative classification) is used to emulate differential dendritic evolution. In this example, 3D per-pixel imaging is used to identify differential changes in dendritic growth across different feature sets. The primary and super-level category differential dendritic evolution we simulate depends on whether the nodes' neural weights are conformed or non-conform.

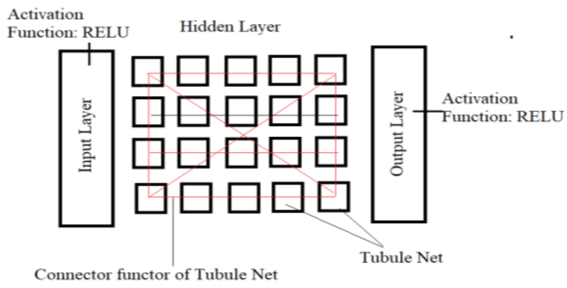


Figure 3. Illustration of sub-modules in Tubule Net

When the activation function of a Tubule Net is triggered, a connection is made to the next Tubule Net in the Tubule Net sequence pool, which is formatted randomly. When the preceding odd activator in every element of the Tubule Net (square box above) actuates over the threshold, the whole Tubule Net will activate over the threshold. From this point, the whole Tubule Net (square box above) will distribute data based on how much each module weighs. For each type of input value received, the threshold value for each module varies. The connection is optimized, and values are stored in the memory. In other words, reply to related input signals vary depending on the series of input signals provided.

3. EXPERIMENTAL SETUP

During the testing, we utilized 4 DJI Parrot drones. Each drone is prohibited by a custom-built autopilot running on Nvidea-Jetson Nano. Each drone's dealing unit contains a quad-core CPU ARM A57 @ 1.43 GHz, Memory of 4 GB 64-bit 64-bitlow-power double data rate (LPDDR4)25.6 GB/s, 4K go pro black Camera units, through Zigbee with Xiaomi repeater for remote streaming of functions, and drone log report. Impartially we require to envelop a 5×5 km region with several drones in a swarm background; thus for the database, we distributed a parse server for real-time transmission among every drone. During the experiment, all drones started from the same position with a purpose to collaboratively cover the slam function in definite land coat. Hence, the drone landing pad is undetermined at the start of the experiment. Also, the battery of every drone can last about 20 minutes at max; as a result, we have program the drones to system the landing region energetically near to one another with a 10-15 m variation.

4. RESULTS AND DISCUSSION

Only the most expensive light detection and ranging (LIDAR) data and vertices and their topological relationships are used, as well as the data and relationships on high-capacity hard drives to reduce costs. A broad range of jobs, including law enforcement, the fire service, and the thermography profession, are becoming substantially more diverse and exciting because of the accessibility to affordable aerial imaging. Using a thermal camera on a drone helps to find missing persons more quickly. Small unmanned aerial vehicles (UAVs) are portable and compact, making them suitable for search and rescue operations. A contribution to law enforcement's mission of encouraging and imposing non-discriminatory polices s for sustainable growth is driven by providing them with the tools and resources they need to accomplish this task. One of the operators takes control of the drone while the other keeps an eye on the downlink feed in the scene to search for signs of life. The drone is controlled by two people who sit at two control stations. However, since visible spectrum cameras cannot distinguish between different lighting conditions, such as foliage, brush, low light, and shadows, it may be challenging to use these cameras in scenes that feature these various conditions, such as foliage, brush, low light and shadows. Making it more challenging to see the contrast is made more difficult by keeping your body temperature and the surrounding environment hidden.

The developed solution brings together the best of worlds (infrared and colored RGB imagery), making the use of infrared imagery easier and allowing pilots to lead others to the target more clearly using landmarks and reference points while also enhancing search operations by increasing the contrast between the imagery and the physical scene. After using the presented solution, results achieved in the 94% natural lighting condition required only 10-15 training samples. The overall digitized map of the Roorkee area from the UAV feed is shown in Figure 4. In Figure 4, the area patrolled by a drone during the night time hours are displayed using a digitized map. The third graphic, which shows the outcomes of the presented mechanism and the currently used state-of-the-art algorithm, is demonstrated in Figure 5.

Figure 6 shows a map of our confidence in the situation. Correlation of map details with the default orthographic photogrammetric method in Figure 6(a) versus presented method Figure 6(b). Every dot represents one test instance. The dashed line at five CPU seconds demonstrates the cut-off time of the objective algorithm utilized amid the setup process.

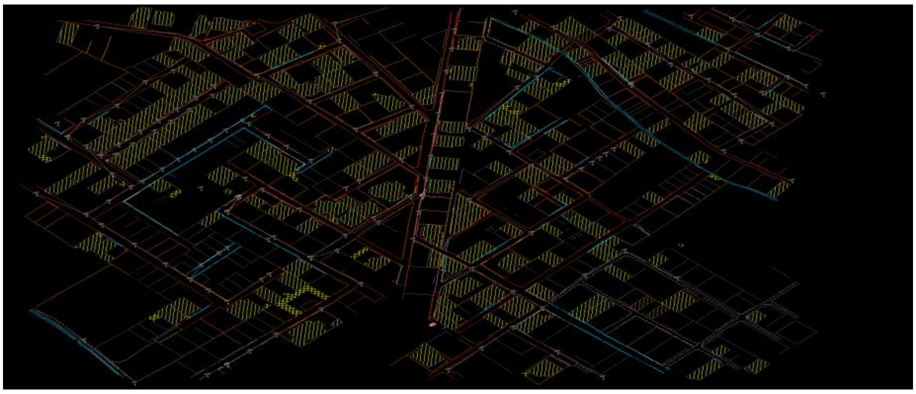


Figure 4. The overall digitized map of the Roorkee area from the UAV feed

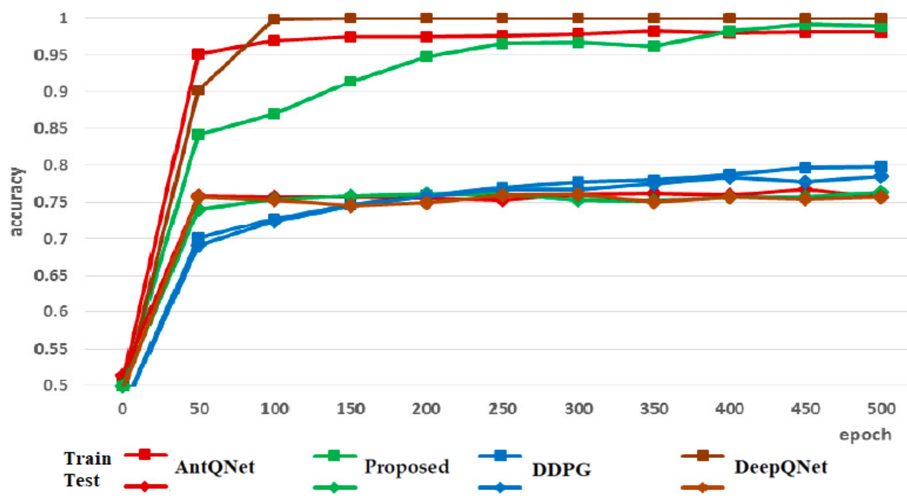
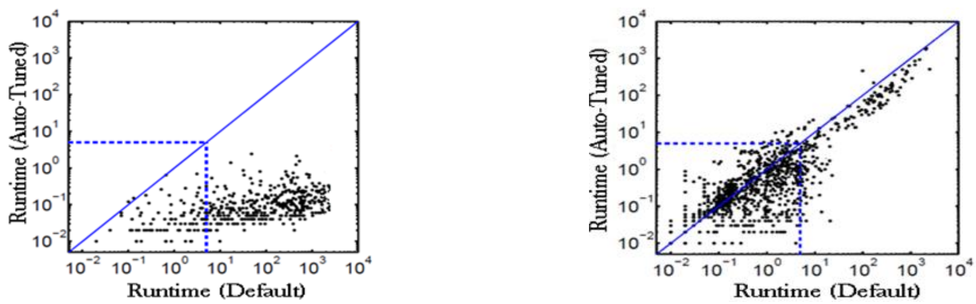


Figure 5. Comparison of the presented mechanism with state-of-the-art algorithms for runtime UAV control and feed digitization



(a) (b)

Figure 6. Correlation of map details with (a) the default orthographic photogrammetric method and (b) the presented method

5. CONCLUSION

This paper exists an auto neural architecture generator for observation in the dark. This allows us to learn how to render accurate edge maps, geometry, and colour while improving our accuracy. The research proposed a soft framework for crisis mapping to aid in mapping the state of the aerial landscape in disaster-stricken areas, allowing strategic rescue operations to be more effectively planned. The digitized map in which pooled edges of the feature classes are retrieved with the pooled set of previous network data to facilitate simple mapping of features, and its following categorization as the missing feature because of poor lighting situation is improved. The outcome of this research fulfills the objective set by United Nations Envision 2030 Goal 16: Peace, Justice, and Strong Institutions. Attenuation of hyper parameter is still a manual burden. This work ensures the expansion of such protocol will enhance the drone mapping in the dark for defense and facilitate solving issue deliberate designing of disaster reactions in tragedy strike regions at night that stays a important issue and the uncharted regions. The future work of this research is to upend the security in the sensing field environment.

REFERENCES

[1] A. V. Savkin and H. Huang, "Navigation of a network of aerial drones for monitoring a frontier of a moving environmental disaster area," *IEEE Systems Journal*, vol. 14, no. 4, pp. 4746–4749, Dec. 2020, doi: 10.1109/JSYST.2020.2966779.

[2] A. V. Savkin and H. Huang, "A method for optimized deployment of a network of surveillance aerial drones," *IEEE Systems Journal*, vol. 13, no. 4, pp. 4474–4477, Dec. 2019, doi: 10.1109/JSYST.2019.2910080.

[3] B. Wang, Y. Yu, and Y.-Q. Xu, "Example-based image color and tone style enhancement," *ACM Transactions on Graphics*, vol. 30, no. 4, pp. 1–12, Jul. 2011, doi: 10.1145/2010324.1964959.

[4] K. Ali, H. X. Nguyen, Q.-T. Vien, P. Shah, and M. Raza, "Deployment of drone-based small cells for public safety communication system," *IEEE Systems Journal*, vol. 14, no. 2, pp. 2882–2891, Jun. 2020, doi: 10.1109/JSYST.2019.2959668.

[5] P. Y. Laffont, Z. Ren, X. Tao, C. Qian, and J. Hays, "Transient attributes for high-level understanding and editing of outdoor scenes," *ACM Transactions on Graphics*, vol. 33, no. 4, pp. 1–11, Jul. 2014, doi: 10.1145/2601097.2601101.

[6] K. Ali, H. X. Nguyen, Q. T. Vien, P. Shah, and Z. Chu, "Disaster management using D2D communication with power transfer and clustering techniques," *IEEE Access*, vol. 6, pp. 14643–14654, 2018, doi: 10.1109/ACCESS.2018.2793532.

[7] B. Sheng, H. Sun, S. Chen, X. Liu, and E. Wu, "Colorization using the rotation-invariant feature space," *IEEE Computer Graphics and Applications*, vol. 31, no. 2, pp. 24–35, Mar. 2011, doi: 10.1109/MCG.2011.18.

[8] S. Ropke and D. Pisinger, "An adaptive large neighborhood search heuristic for the pickup and delivery problem with time windows," *Transportation Science*, vol. 40, no. 4, pp. 455–472, Nov. 2006, doi: 10.1287/trsc.1050.0135.

[9] A. Deshpande, J. Rock, and D. Forsyth, "Learning large-scale automatic image colorization," in *2015 IEEE International Conference on Computer Vision (ICCV)*, Dec. 2015, pp. 567–575, doi: 10.1109/ICCV.2015.72.

[10] Z. Cheng, Q. Yang, and B. Sheng, "Deep colorization," in *2015 IEEE International Conference on Computer Vision (ICCV)*, Dec. 2015, pp. 415–423, doi: 10.1109/ICCV.2015.55.

[11] G. Patterson and J. Hays, "SUN attribute database: discovering, annotating, and recognizing scene attributes," in *2012 IEEE Conference on Computer Vision and Pattern Recognition*, Jun. 2012, pp. 2751–2758, doi: 10.1109/CVPR.2012.6247998.

[12] E. Tola, V. Lepetit, and P. Fua, "A fast local descriptor for dense matching," in *2008 IEEE Conference on Computer Vision and Pattern Recognition*, Jun. 2008, pp. 1–8, doi: 10.1109/CVPR.2008.4587673.

[13] R. Dahl, "Automatic colorization," *tinyclouds.org*, 2016. https://tinyclouds.org/colorize.

[14] S. Iizuka, E. Simo-Serra, and H. Ishikawa, "Let there be color!," *ACM Transactions on Graphics*, vol. 35, no. 4, pp. 1–11, Jul. 2016, doi: 10.1145/2897824.2925974.

[15] V. Bhavana and H. K. Krishnappa, "Multi-modal image fusion using contourlet and wavelet transforms: a multi-resolution approach," *Indonesian Journal of Electrical Engineering and Computer Science (IJEECS)*, vol. 28, no. 2, pp. 762–768, Nov. 2022, doi: 10.11591/ijeecs.v28.i2.pp762-768.

[16] E. Abana and B. Sy, "ISO/IEC 25010 based evaluation of rice seed analyzer: a machine vision application using image processing technique," *Indonesian Journal of Electrical Engineering and Computer Science (IJEECS)*, vol. 28, no. 2, pp. 994–1001, Nov. 2022, doi: 10.11591/ijeecs.v28.i2.pp994-1001.

[17] S. Thomas and A. Krishna, "Impulse noise recuperation from grayscale and medical images using supervised curve fitting linear regression and mean filter," *Indonesian Journal of Electrical Engineering and Computer Science (IJEECS)*, vol. 28, no. 2, pp. 777–786, Nov. 2022, doi: 10.11591/ijeecs.v28.i2.pp777-786.

[18] A. Rai and R. J. Kannan, "Auto neural architecture generator for UAV-based geospatial surveillance for aerial crisis mapping in dark," *Journal of the Indian Society of Remote Sensing*, vol. 49, no. 3, pp. 507–514, Mar. 2021, doi: 10.1007/s12524-020-01236-y.

[19] R. Raman, S. Muthumarilakshmi, G. Jethava, R. Jagtap, M. Lalitha, and S. Murugan, "Energy monitoring in solar-powered buildings using internet of things," in *2023 2nd International Conference on Smart Technologies for Smart Nation, SmartTechCon 2023*, 2023, pp. 318–322, doi: 10.1109/SmartTechCon57526.2023.10391826.

[20] V. G. Sivakumar, V. V. Baskar, M. Vadivel, S. P. Vimal, and S. Murugan, "IoT and GIS integration for real-time monitoring of soil health and nutrient status," in *2023 International Conference on Self Sustainable Artificial Intelligence Systems (ICSSAS)*, Oct. 2023, pp. 1265–1270, doi: 10.1109/ICSSAS57918.2023.10331694.

[21] R. K. Vanakamamidi, L. Ramalingam, N. Abirami, S. Priyanka, C. S. Kumar, and S. Murugan, "IoT security based on machine learning," in *2023 Second International Conference On Smart Technologies For Smart Nation (SmartTechCon)*, Aug. 2023, pp. 683–687, doi: 10.1109/SmartTechCon57526.2023.10391727.

[22] T. R. Saravanan, A. R. Rathinam, J. Lenin, A. Komathi, B. Bharathi, and S. Murugan, "Revolutionizing cloud computing: evaluating the influence of blockchain and consensus algorithms," in *2023 3rd International Conference on Smart Generation Computing, Communication and Networking (SMART GENCON)*, Dec. 2023, pp. 1–6, doi: 10.1109/SMARTGENCON60755.2023.10442008.

[23] C. C. Sekhar, V. V, K. Vijayalakshmi, M. B. Sahaai, A. S. Rao, and S. Murugan, "Cloud-based water tank management and control system," in *2023 Second International Conference On Smart Technologies For Smart Nation (SmartTechCon)*, Aug. 2023, pp. 641–646, doi: 10.1109/SmartTechCon57526.2023.10391730.

[24] T. Meenakshi, R. Ramani, A. Karthikeyan, N. S. Vanitha, and S. Murugan, "Power quality monitoring of a photovoltaic system through IoT," in *2023 International Conference on Sustainable Communication Networks and Application (ICSCNA)*, Nov. 2023, pp. 413–418, doi: 10.1109/ICSCNA58489.2023.10370494.

[25] R. Raman, V. Sujatha, C. B. Thacker, K. Bikram, M. B. Sahaai, and S. Murugan, "Intelligent parking management systems using IoT and machine learning techniques for real-time space availability estimation," in *2023 International Conference on Sustainable Communication Networks and Application (ICSCNA)*, Nov. 2023, pp. 286–291, doi: 10.1109/ICSCNA58489.2023.10370636.

[26] A. Karthikeyan, N. S. Vanitha, T. Meenakshi, R. Ramani, and S. Murugan, "Electric vehicle battery charging in grid system using fuzzy based bidirectional converter," in *2023 3rd International Conference on Innovative Mechanisms for Industry Applications (ICIMIA)*, Dec. 2023, pp. 1447–1452, doi: 10.1109/ICIMIA60377.2023.10426581.

BIOGRAPHIES OF AUTHORS

Dr. Raju Jagadeesh Kannan is a senior IEEE member, working as Sr. Professor in Department of Computer Science and Engineering and Dean, Engineering and Technology at SRM Institute of Science and Technology Tiruchirappalli. He received Bachelor of Engineering in Instrumentation and Control Engineering from Madurai Kamaraj University, Madurai, Tamilnadu, India. He secured Master of Engineering in Computer Science and Engineering at Manonmaniam Sundaranar University, Tirunelveli, Tamilnadu, India. He was awarded Ph.D. in the field of Computer Science and Engineering at Anna University, Chennai, Tamilnadu India. He carries both industry and academic experience for more than 20 years. He has presented 170 papers in national and international journals, conference and symposiums. He chaired session track in conferences of national and international repute and served as reviewer for peer-reviewed journals. His major area of interest includes cyber physical systems, computational intelligence, and imaging and computer vision. He can be contacted at email: jagadeeshkannan.r@vit.ac.in.

Prof. Karunesh Pratap Yadav received (Vishwa Guru: awarded and recognized from USA) is B.Tech., PGDBM, M.Tech., Ph.D. and Post Doctorate D.Sc. and D.Litt. Also, having Hon. Doctorates like D.Sc. /D.Litt./ Ph.D. from International Universities/Institutes: Engineering, Life Science and Health Science, Education and Management, Humanities and Management, Agriculture, and Advocacy/Law. Presently, Prof. Yadav is Vice Chancellor of MATS University, Raipur CG (second term VC)along with Hon'ble President of India Nominee for Indian Institute of Information Technology(IIIT) Tiruchirapalli, Hon'ble Governor of Chhattisgarh Nominee as Board Member of Govt. Mahatma Gandhi Horticulture and Forestry University Raipur/Durg and Margdarshak of All India Council for Technical Education (AICTE) New Delhi: Margdarshak of Rajasthan Technical University Kota and SSPITM Raipur, Mardarshak of Hindi Sahitya Bharati for Rajasthan State, Advisor/Directorship to Kingdom Life Christian University Inc. Hon'ble President of India/Visitor's Nominee for Indian Institute of Information Technology (IIIT), Tiruchirapalli, Tamilnadu. Hon'ble CG Governor's Nominee for Mahatma Gandhi University of Horticulture and Forestry, Durg/Raipur, Chhattisgarh. And Country Head, India of Yesbud University (Equal to VC), Lusaca, Zambia, South Africa. He has 27+ years of experience in teaching, research, administration and industry. He was Director for 8 years in different Engineering/Management Institutes (AICTE Approved) at NCR Delhi region (ACE, SIET Ghaziabad, and MIET, KCCITM, IIMT Greater Noida) and former Vice Chancellor/President of Sangam University, Bhilwara, Rajasthan. His expertise is NAAC/AICTE-NBA/ABET/NIRF/ICAR/BCI/QS Star International like accreditation and ranking systems. He can be contacted at email: drkpyadav732@gmail.com.

Dr. Balasubramanian Sreedevi is presently working as professor and HOD in Department of Computer Science and Engineering at Sri Sai Ram Institute of Technology. She completed her Master's Degree in Computer Science and Engineering with Distinction from SRM University and obtained Ph.D. degree in Computer Science and Engineering from Anna University, Chennai, and Tamilnadu, India. She has more than 18years of experience in teaching and software industry. She has published papers in Scopus (SCI) and IEEE. Her research interest's lies in the area of programming languages, machine learning and image processing. She has collaborated actively with researchers in several other disciplines of computer science, particularly medical imaging. She has published 5 patents and authored books and book chapters. She is an active member of many professional bodies like ISTE, CSI, IEI, IEEE, IAENG, and IRO. She can be contacted at email: hodcse@sairamit.edu.in.

Dr. Jehan Chelliah received the BE degree in the Department of Electronics and Communication Engineering from Madurai Kamaraj University, Tamil Nadu, India in 1992. He completed ME degree in the Department of Electronics and Communication Engineering from Madurai Kamaraj University, Tamil Nadu, India in 1999 and obtained the Ph.D. degree in the Department of Information and Communication from the Manonmanium Sundaranar University, Tirunelveli, Tamil Nadu, India in 2017. He is currently working in the Department of Computer Science and Engineering at at Vel tech Multitech Dr. Rangarajen Dr. Sakunthala Engineering College, Avadi, Chennai. His research interests are in wireless sensor networks, machine learning, deep learning, and data mining. He has published more Scopus, SCI, and WoS journals. He can be contacted at email: Cjehan2001@gmail.com.

Dr. Surulivelu Muthumarilakshmi is an associate professor in Computer Science and Engineering at Chennai Institute of Technology, Kundrathur. With over 13 years of teaching experience, her primary focus revolves around computer networks. He is particularly interested in investigating network protocols, security measures, and ways to optimize network performance. Her passion lies in researching and publishing articles that delve into these areas, aiming to enhance our understanding of robust network systems and contribute valuable insights to the academic community. She can be contacted at email: muthu3041974@gmail.com.

Dr. Jeyaprakash Jeyapriya is a ISTE member, working as a ML Engineer, Apcomart Private Limited, Bangalore. She received Bachelor of Engineering in Computer Science and Engineering from Anna University, Chennai, Tamilnadu, India. She secured Master of Engineering in Computer Science and Engineering at Anna University, Chennai, Tamilnadu, India. She was awarded Ph.D. in the field of Computer Science and Engineering at VIT University, Vellore, Tamilnadu India. She carries academic experience for more than 8 years. She has presented 10 papers in national and international journals, conference and symposiums. Her major area of interest includes computational intelligence, and imaging and computer vision. She can be contacted at email: priyacseme@gmail.com.

Subbiah Murugan is an adjunct professor, Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, Chennai, Tamilnadu, India. He published his research articles in many international and national conferences and journals. His research areas include network security and machine learning. He can be contacted at email: smuresjur@gmail.com.