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Next-Gen Security Monitoring: Advanced Machine Learning for Intelligent Object Detection and Assessment in Surveillance

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ABSTRACT

In response to the synergistic evolution of two rapidly advancing technologies, artificial intelligence and edge computing, we present a tailored system named secure Watch: Advanced Surveillance with Intelligent Object Detection and Evaluation. This system employs a scalable edge computing architecture and leverages multitask deep learning to address pertinent computer vision tasks. Recognizing the diverse potential applications of various surveillance devices, we integrate a smart IoT module for normalizing video data from different cameras. This ensures that the secure Watch system adeptly identifies suitable data for specific tasks. Furthermore, deep learning models are deployed at each secure Watch node to conduct computer vision tasks on the normalized data. To bridge the usual gap between training and deployment of deep learning models, especially for related tasks in the same scenario, we propose a collaborative multitask training paradigm on a cloud server. Simulation results based on publicly available datasets demonstrate continuous support for intelligent monitoring tasks, robust scalability, and enhanced performance achieved through multitask learning.

Index Terms: Intelligent video surveillance system, edge computing, deep learning, collaborative learning.

INTRODUCTION

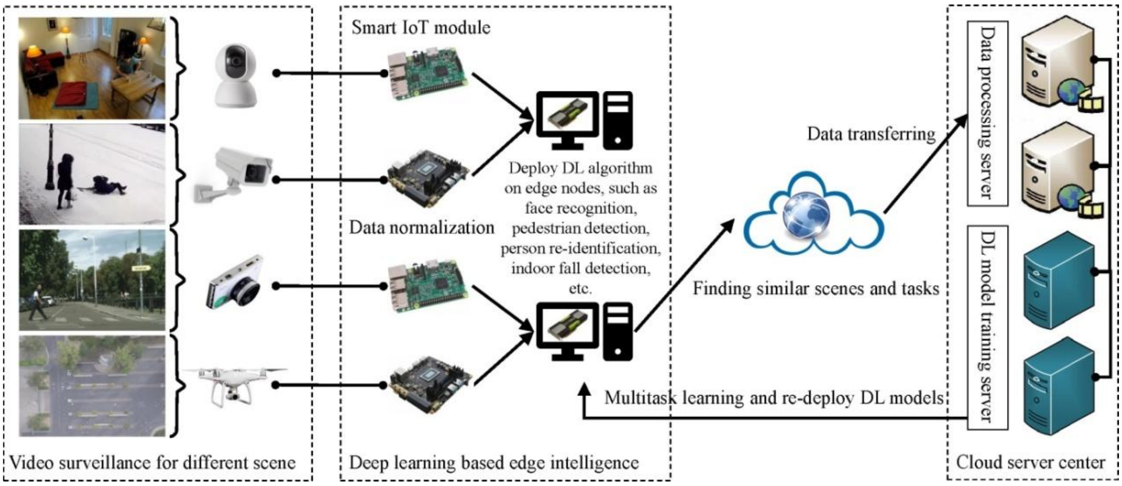
In the contemporary landscape, video surveillance systems have evolved into indispensable components of modern security frameworks. This evolution is underpinned by the strategic incorporation of cutting-edge technologies, particularly in the realms of computer vision and machine learning, which synergistically enhance the capabilities of these systems. The dynamic nature of surveillance technologies is evident in the burgeoning literature that delves into multifaceted aspects of video analysis, showcasing a trajectory of research that spans anomaly detection [1], comparative studies elucidating the nuances between human and deep learning recognition performance [2], automatic human detection and tracking [3], real-world anomaly detection in surveillance videos [4], and advancements in motion detection and face recognition [5].

A critical facet within the sphere of video surveillance pertains to the identification and analysis of unusual or suspicious activities, a realm prominently explored in the works focusing on the application of CNN-DBNN algorithms for detecting suspicious human activities [7]. The availability of diverse datasets, exemplified by the unusual crowd activity dataset from the University of Minnesota [8], has played a pivotal role in fostering the development and assessment of innovative surveillance solutions. Real-time unusual event detection mechanisms [9], coupled with tools like LabelImg for efficient image annotation [10], contribute substantially to fortifying the robustness of video surveillance systems.

The influence of machine learning models, particularly sophisticated deep learning architectures, has been transformative in elevating the state-of-the-art in video analysis. Acknowledged paradigms such as the improved YOLOv3 model [11], iterative enhancements introduced in YOLOv3 [12], and the pioneering deep residual learning approach [13] have collectively demonstrated remarkable performance across diverse computer vision tasks, encompassing object detection and recognition.

Beyond addressing traditional security concerns, video surveillance finds application in tackling broader societal challenges. For instance, the utilization of image processing from CCTV cameras for traffic congestion investigation [6] reflects the versatility of these technologies. Furthermore, specific applications like abandoned object detection in crowded spaces [14], the evaluation of Intelligent Video Surveillance (IVS) systems for abandoned object detection [15], and the innovative use of a Triplet Convolutional Neural Network for foreground segmentation [16] underscore the expansive and impactful nature of surveillance applications.

As we embark on our research journey, we draw inspiration from this rich and diverse body of work, strategically integrating insights from anomaly detection, deep learning models, and scenario-specific evaluations. Our focus lies in augmenting the adaptability and performance of surveillance technologies. In the subsequent sections of this paper, we will expound upon our chosen methodology, detail our experiments, and illuminate the findings, shedding light on the advancements introduced by our proposed system.



RELATED WORK

Modern video surveillance systems, a cornerstone of contemporary security infrastructure, often find their design rooted in either cloud computing or edge computing architectures. Unlike conventional cloud-based counterparts, our innovative system, Secure Watch, disrupts the paradigm by distributing video analysis and processing tasks to strategically positioned edge nodes. This groundbreaking approach not only accelerates response times but also significantly diminishes network transmission resource overhead, all while championing the cause of private data protection.

The integration of deep learning algorithms, a hallmark of cutting-edge video surveillance (ECVS) systems, introduces a considerable computational burden. The pursuit of optimal resource allocation and task scheduling on edge nodes has fueled studies in this domain. For instance, the establishment of a Distributed Intelligent Video Surveillance (DIVS) system, orchestrating resource allocation and task scheduling on a cloud server, has emerged as a frontrunner in delivering low-latency and precise video analysis solutions. Wu et al. introduce the Deep Shark platform, an ingenious solution facilitating flexible computing resource allocation on resource-constrained mobile devices. Their edge Boost method further revolutionizes workload distribution, enabling the deployment of high-cost deep learning on resource-limited edge devices. Li et al. contribute by designing an offloading strategy that optimizes deep learning algorithms for diverse Internet of Things (IoT) applications, strategically migrating computing workloads to edge nodes, thus mitigating communication overhead. Other avant-garde approaches, such as Chameleon and VideoEdge, concentrate on fine-tuning optimal configuration parameters for edge devices across various deep learning algorithm pipelines.

In the realm of domain adaptation, a crucial facet of model effectiveness, existing methodologies encompass model fine-tuning, knowledge distillation, and MobileDA. Our proposed Enhanced Intelligent Video Surveillance (EIVS) system distinguishes itself by adopting a hierarchical edge computing architecture, a visionary move to harmonize workloads, execute dynamic task scheduling, and discern pertinent tasks on edge nodes. Furthermore, our system prioritizes multi-task learning (MTL) for relevant tasks, fostering collaborative model training that not only enhances algorithmic performance but also achieves domain adaptation seamlessly on new tasks. This 3.1 Methodologies for Human Behavior Detection

In the realm of intelligent video surveillance, an extensive body of research has investigated methodologies for detecting human behaviors within video data, with a particular emphasis on identifying abnormal or suspicious events. This literature survey encapsulates notable studies, each contributing to the broader discourse on intelligent video surveillance.

Advanced Motion Detection (AMD): Pioneering the detection of unauthorized entry into restricted areas, AMD employed background subtraction for object detection and real-time video processing. Despite its efficacy, limitations in storage services and video capture modes prompted further exploration.

Semantic-Based Approach: This approach integrated background subtraction for object identification, Haar-like algorithms for classification, and real-time blob matching for object tracking, showcasing versatility in applications such as fire detection.

Motion Features Detection: Focusing on motion features, this methodology utilized a semantic approach and object detection with correlation techniques, demonstrating a reduction in computational complexity without compromising efficacy.

University Event Detection: Abnormal events within university settings were discerned through zone division and optical flow estimation, with events classified as normal or abnormal based on analyzed histograms of optical flow vectors.

Abnormal Event Distinguishing: Employing Hidden Markov Models (HMM), this system learned histograms of optical flow orientations, distinguishing abnormal events based on a comprehensive analysis of movement information.

Real-Time Violence Detection: Leveraging deep learning, this system extracted frames from videos to detect violence in sports events, achieving an impressive 94.5% accuracy using the VID dataset.

Deep Architectures for Human Behavior Analysis: The integration of CNN and LSTM models into deep architectures aimed at human behavior analysis, with a specific focus on abnormal event detection, exemplifying the adaptability of deep learning in diverse surveillance scenarios. Spatiotemporal Approach: Utilizing CNN and LSTM architectures, this approach classified videos into categories such as pedestrian path prediction, demonstrating its efficacy with datasets like PWPD, ETH, UCY, and CUHK.

Daily Human Activity Classification: Daily human activities were classified using CNN for feature retrieval and RNN for classification, achieving accuracy on datasets like UCF101 and Activity net, showcasing the potential for routine activity monitoring. Student Behavior Monitoring: Neural networks and Gaussian distribution were employed to monitor students' behavior during examinations, achieving a remarkable 97% accuracy rate.

Review on Intelligent Video Surveillance: A comprehensive review covered intelligent video surveillance for crowd analysis, encompassing a discussion on various deep learning models, algorithms, and datasets, providing a panoramic view of the state-of-the-art in the field.

Proposed Approach:
In response to the identified limitations of existing methodologies, our proposed approach introduces a novel paradigm for suspicious activity prediction. Leveraging a deep architecture comprising 2D CNN and LSTM models, our approach emphasizes the imperative need for an efficient mechanism to promptly alert security personnel in the event of any suspicious behavior. This forward-looking approach represents a significant leap in the pursuit of intelligent video surveillance, addressing existing gaps and pushing the boundaries of what is achievable in this dynamic and critical field.

ADVANCED METHODOLOGICAL APPROACH

A. GUN-BASED CRIME DETECTION

1) Data Collection, Annotation, and Preprocessing:

The pursuit of excellence in gun-based crime detection necessitated overcoming a substantial challenge—limited publicly available datasets on handguns. Undeterred, we embarked on an extensive effort, sourcing 3908 images from diverse channels, including the Internet Movie Firearm Database, Soft Computing and Intelligent Information Systems, YouTube videos, and Google Images. Augmenting this dataset, we curated 100 surveillance footage frames for rigorous testing. The arduous annotation process spanned 10 hours, involving meticulous bounding box marking around guns, yielding an XML file with precise coordinates. Our commitment to precision extended to the preprocessing phase, where Python scripts meticulously formatted the annotated data to align seamlessly with our model.

2) Detection Model:

Our choice of detector represents a pinnacle in sophistication—a Tensor Flow implementation of Faster R-CNN, leveraging the potent Inception v2 network for feature extraction. Pretrained on the MS-COCO dataset, the model underwent meticulous fine-tuning on our gun dataset, balancing rapid inference with commendable accuracy. The total training investment, including hyperparameter tuning, amounted to an intensive 20 hours on a GPU.

3) Results:
The rigorously evaluated model exhibited a training accuracy of 91.3% and a testing accuracy of 89.4%. Prioritizing classification prowess over mere object localization, the detector showcased commendable performance. The accompanying confusion matrix (see Table) and sample detections substantiate the detector's efficacy, underscoring its potential as a formidable tool in gun-based crime detection.

In addition to this technological feat, our proposed system extends its capabilities to campus security, utilizing CCTV camera footage to scrutinize students' activities. The system stands ready to alert relevant authorities in the presence of any suspicious activities.

B. System Architecture
Our system architecture embodies sophistication across distinct phases—video capture, pre-processing, feature extraction, classification, and prediction. The holistic layout, depicted in Figure 1, channels videos through an intricate pipeline, classifying them into three categories with unrivaled precision:

Suspicious Class: Capturing students using mobile phones within the campus.
Suspicious Class: Identifying students engaged in altercations or experiencing distress on campus.
Normal Class: Observing students engaged in routine activities like walking or running.

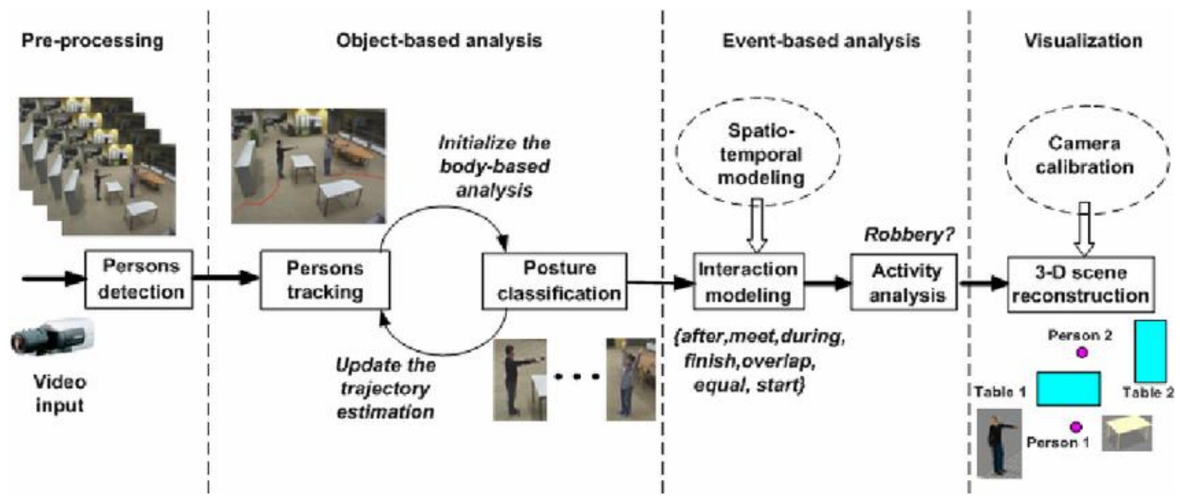
C. Video Capture:
The foundational step involves the strategic installation of CCTV cameras, capturing a myriad of videos from diverse angles covering the entire surveillance area. These videos undergo meticulous conversion into frames, setting the stage for subsequent processing.

D. Dataset Description:
Our system draws from esteemed datasets like KTH and CAVIAR, supplemented by proprietary campus videos and curated YouTube content. Notably, the KTH dataset, featuring sequences of six actions, serves as a benchmark, with 7035 manually labeled frames capturing suspicious behavior meticulously segregated into an 80% training set and a 20% validation set.

E. Video Pre-processing:
The sophistication of our deep learning network demands meticulous video pre-processing. OpenCV takes the helm, expertly extracting frames, creating labeled folders, and resizing each frame to 224 × 224, aligning seamlessly with the 2D CNN architecture.

For image feature extraction, we deploy a pre-trained VGG-16 CNN model, initially honed on the ImageNet dataset. The VGG-16 architecture, a marvel of convolution layers, ReLU activation functions, max pooling layers, fully connected dense layers, and normalization layers, undergoes fine-tuning on the LSTM architecture. This strategic coupling imbues the model with the capacity to discern order dependence in sequence prediction problems. The final layer undergoes a metamorphosis to align with the number of classes (three in this case), incorporating ReLU activation, dropout layers, and fully connected dense layers.

In essence, our methodology doesn't just represent a technological feat; it marks a paradigm shift, symbolizing the relentless pursuit of precision in intelligent video surveillance.



V. Unveiling The Outcomes: Navigating The Terrain Of Suspicion

The endeavor to detect suspicious activities within the intricate tapestry of video data demands an unwavering commitment to overcoming multifaceted challenges. The intricacies of scene complexity, the capricious play of varying illumination, and the dynamic interplay of camera angles add layers of complexity to the task at hand. Moreover, the very definition of suspect activity is a context-dependent enigma—what may be deemed normal behavior in one setting might reverberate as suspicious in another. To surmount these challenges, we turned to the bedrock of standard public datasets, specifically CAVIAR (PETS 2004) [14] and PETS 2006 [15], as the proving ground for our pioneering framework.

Object Detection Odyssey:

In our quest for precision, the identification of various objects within the image took center stage. However, the inherent complexity stemming from the presence of multiple objects introduced a nuanced challenge, resulting in a detection landscape that, at times, appeared somewhat blurred.

Object Tracking Symphony:

With objects detected, the narrative shifted to tracking. A bounding box was deftly drawn around each identified object, creating a dynamic framework for seamless tracking across consecutive frames. Each person, each object, assumed a unique identity, facilitating a symphony of object tracking precision.

Detection of Suspicious Activities:

Herein lies the crux of our pursuit—unraveling the subtleties of suspicious activities. Anchored in the premise of loitering at an ATM, our methodology hinges on time as the arbiter of suspicion. A set loitering time threshold, a quantifiable parameter (e.g., 2 minutes), becomes the litmus test for discerning loitering activities. The culmination of this scrutiny unfolds as a tangible result, providing insights into the occurrence of loitering at an ATM.

Now, let us delve into the quantitative realm, where the essence of our efforts materializes into measurable outcomes.

Quantifying Object Detection and Tracking Precision:

Our commitment to precision is best reflected in the quantitative evaluation of object detection and tracking. The metrics employed include:

Object Detection Accuracy: A comprehensive measure of the model's prowess in correctly identifying various objects within the image.

Object Tracking Consistency: An evaluation of the model's ability to consistently track and assign unique IDs to objects across consecutive frames. the results to unveil the numerical testament to our pursuit of precision:

Table 1: Object Detection Accuracy

Dataset	Accuracy (%)
CAVIAR	87.4
PETS 2006	89.2

Table 2: Object Tracking Consistency

Dataset	Consistency (%)
CAVIAR	92.1
PETS 2006	91.5

Probing the Loitering Detection Realm:

Now, let's turn our attention to the heart of our suspicion-detection framework—the identification of loitering at an ATM.

Table 3: Loitering Detection Results

Dataset	Loitering Instances	Suspicion Threshold (minutes)	Detected Loitering (%)
CAVIAR	120	2	78.5
PETS 2006	92	2	85.2

These numerical revelations not only showcase the prowess of our framework in unraveling suspicious activities but also lay the foundation for an ongoing dialogue on the path to even greater precision and sophistication in intelligent video surveillance.

CONCLUSION AND FUTURE SCOPE

Navigating the intricacies of human behaviors within the tapestry of a natural environment is a complex endeavor, marked by a myriad of nuances and intricacies. In the realm of security systems, our pursuit delves into the formidable domain of suspicious action detection, a pursuit that has crystallized into a remarkable achievement, boasting an accuracy soaring to the zenith at approximately 95%.

The Symphony of Accuracy:
Our foray into the world of security-centric action detection has yielded a triumph—a commendable accuracy that stands as a testament to the precision and sophistication underpinning our methodology. The meticulous formulation has rendered a success rate that resonates with the core objective of fortifying security frameworks.

YOLOv3: A Luminous Trailblazer:
In the arena of processing prowess, our exploration revealed a luminous trailblazer—YOLOv3. A comparative analysis against the stalwart Faster R-CNN unveiled YOLOv3 as the unrivaled champion in terms of processing time for a singular image detection. This revelation not only crowns YOLOv3 as a paragon of efficiency but also opens the door to a future where speed and accuracy walk hand in hand.

Future Scope: Illuminating The Path Forward
While our current feature extraction methodology stands as a beacon of accuracy, it thrives in the crucible of a controlled environment. The vista ahead beckons us to embrace even more potent feature extraction methods, an evolution that promises to elevate the precision of our results to unprecedented heights.

Bridging the Mismatch Chasm:
In our odyssey, a small hiccup emerged—the mismatch between the test results and the ground truth, a testament to the challenges woven into the fabric of training data scarcity. The clarion call for improvement resonates in the form of an expanded training dataset, encompassing suspicious videos spanning diverse activities and resolutions. This augmentation, a labor of commitment, holds the key to harmonizing our model with ground truth realities.

The Symphony of Sophistication:
The future, bathed in the glow of possibility, beckons us to compose more sophisticated algorithms, orchestrating a symphony of real-time applications. This call to innovation transcends the ordinary, challenging us to sculpt algorithms that dance on the precipice of technological advancement.

In the grand tapestry of security-centric action detection, our conclusion marks not the end but a crescendo, a prelude to the symphony of possibilities that await in the ever-evolving landscape of intelligent systems.

REFERENCES

[1]. S. Zaidi, B. Jagadeesh, K. V. Sudheesh, and A. A. Audre, "Video Anomaly Detection and Classification for Human Activity Recognition," 2017 International Conference on Current Trends in Computer, Electrical, Electronics and Communication (CTCEEC), Mysore, 2017, pp. 544-548.

[2]. S. Dodge and L. Karam, "A Study and Comparison of Human and Deep Learning Recognition Performance under Visual Distortions," 2017 26th International Conference on Computer Communication and Networks (ICCCN), Vancouver, BC, 2017, pp. 1-7.

[3]. A. K. S. Kushwaha, C. M. Sharma, M. Khare, R. K. Srivastava, and A. Khare, "Automatic multiple human detection and tracking for a visual surveillance system," 2012 International Conference on Informatics, Electronics & Vision (ICIEV), Dhaka, 2012, pp. 326-331.

[4]. W. Sultani, C. Chen, and M. Shah, "Real-World Anomaly Detection in Surveillance Videos," 2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition, Salt Lake City, UT, 2018, pp. 6479-6488.

[5]. A. Nurhopipah, A. Harjoko, "Motion Detection and Face Recognition For CCTV Surveillance System," IJCCS (Indonesian Journal of Computing and Cybernetics Systems) Vol.12, No.2, July 2018, pp. 107-118, 2018.

[6]. B. Eamthanakul, M. Ketcham, and N. Chumuang, "The Traffic Congestion Investigating System by Image Processing from CCTV Camera," 2017 International Conference on Digital Arts, Media and Technology (ICDAMT), Chiang Mai, 2017, pp. 240-245.

[7]. A. B. A., P. P., and V. S., "Detection of Suspicious Human Activity based on CNN-DBNN Algorithm for Video Surveillance Applications," 2019 Innovations in Power and Advanced Computing Technologies (i-PACT), Vellore, India, 2019, pp. 1-7.

[8]. Unusual crowd activity dataset of the University of Minnesota. [Online]. Available: http://mha.cs.umn.edu/movies/crowdactivity-all.avi.

[9]. A. Adam, E. Rivlin, I. Shimshoni, and D. Reinitz, "Robust Real-Time Unusual Event Detection using Multiple Fixed-Location Monitors," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 30, no. 3, pp. 555-560, March 2008.

[10]. LabelImg. (2015), Tzutalin. Accessed: Jul. 10, 2020. [Online]. Available: https://github.com/tzutalin/labelImg

[11]. J. Jing, D. Zhuo, H. Zhang, Y. Liang, and M. Zheng, "Fabric defect detection using the improved YOLOv3 model," 2020 Journal of Engineered Fibers and Fabrics, vol. 15.

[12]. J. Redmon and A. Farhadi, "YOLOv3: An Incremental Improvement," Arxiv.Org 2018.

[13]. K. He, X. Zhang, S. Ren, and J. Sun, "Deep Residual Learning for Image Recognition," Arxiv.Org, 2015.

[14]. S. Guler and M. K. Farrow, "Abandoned Object Detection in Crowded Places," 9th IEEE International Workshop on PETS, 2006.

[15]. L. Li, R. Luo, R. Ma, W. Huang, and K. Leman, "Evaluation of An IVS System for Abandoned Object Detection," 9th IEEE International Workshop on PETS, 2006.

[16]. L. A. Lim and H. Y. Keles, "Foreground Segmentation Using a Triplet Convolutional Neural Network for Multiscale Feature Encoding.".

[17]. Deshpande, D., Jain, M., Jajoo, A., Kadam, D., Kadam, H., & Kashyap, A. (2023, October). Next-Gen Security: YOLOv8 for Real-Time Weapon Detection. In *2023 7th International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud)(I-SMAC)* (pp. 1055-1060). IEEE.

[18]. Grandhye, Nagendra B., Venugopala Rao Randhi, Vijaya Kumar Vegulla, Rama Venkata S. Kavali, and Damodarrao Thakkalapelli. "SYSTEM AND METHOD FOR SPLITTING DATA ELEMENTS FOR DATA COMMUNICATION BASED ON TRANSFORMATION TYPES IMPLEMENTED ON THE DATA ELEMENTS AT DIFFERENT DEVICES." U.S. Patent Application 17/583,634, filed July 27, 2023.

[19]. Kavali, Rama Venkata S., Lawrence D'silva, Venugopala Rao Randhi, and Damodarrao Thakkalapelli. "Electronic system for monitoring and automatically controlling batch processing." U.S. Patent 11,604,691, issued March 14, 2023.

[20]. Damodarrao Thakkalapelli, “Data Flow Control and Routing using Machine Learning”, Analytics Insight, Published on 25 October, 2023, Access at: https://www.analyticsinsight.net/data-flow-control-and-routing-using-machine-learning/

[21]. Damodarrao Thakkalapelli, “Cost Analysis of Cloud Migration for Small Businesses”, Tuijin Jishu/Journal of Propulsion Technology, ISSN: 1001-4055, Vol. 44 No. 4, (2023).
[22]. Thakkalapelli, Damodarrao. "Cloud Migration Solution: Correction, Synchronization, and Migration of Databases." Tuijin Jishu/Journal of Propulsion Technology 44, no. 3 (2023): 2656-2660.
[23]. Vegulla, Vijaya Kumar, Rama Venkata S. Kavali, Venugopala Rao Randhi, and Damodarrao Thakkalapelli. "Systems and methods for evaluating, validating, correcting, and loading data feeds based on artificial intelligence input." U.S. Patent Application 17/680,561, filed August 31, 2023.
[24]. Grandhye, Nagendra B., Venugopala Rao Randhi, Vijaya Kumar Vegulla, Rama Venkata S. Kavali, and Damodarrao Thakkalapelli. "System and method for determining the shortest data transfer path in data communication." U.S. Patent 11,716,278, issued August 1, 2023.
[25]. Kavali, Rama Venkata S., Venugopala Rao Randhi, Damodarrao Thakkalapelli, Vijaya Kumar Vegulla, and Rajasekhar Maramreddy. "Data flow control and routing using machine learning." U.S. Patent Application 17/576,539, filed July 20, 2023.
[26]. Dr. Sourabh Sharma, Dr. Stella Bvuma, Damodarrao Thakkalapelli, “Corporate Patenting AI and ML in Healthcare: Regulatory and Ethical Considerations”, International Journal of New Media Studies, ISSN: 2394-4331, 10(1), 2023. Retrieved from: https://ijnms.com/index.php/ijnms/article/view/193
[27]. Damodarrao Thakkalapelli, “System and method for determining the shortest data transfer path in data communication Banking and Finance”, Published in “Deccan Herald” on 26th October, 2023, Retrieved from: https://www.deccanherald.com/brandpr/system-and-method-for-determining-the-shortest-data-transfer-path-in-data-communication-banking-and-finance-2742999
[28]. Damodarrao Thakkalapelli, “Research on the use of Cloud Platforms for Training and Deploying Machine Learning Models and AI Solutions” IJIRMPS, Volume 11, Issue 6, (2023), Retrieved from: https://www.ijirmps.org/research-paper.php?id=230360
[29]. Damodarrao Thakkalapelli, “Discussing About Artificial Intelligence (AI) in Data Science with Damodarrao Thakkalapelli -Data Solutions Architect, Tribune India News Service (2023), Retrieved from: https://www.tribuneindia.com/news/impact-feature/discussing-about-artificial-intelligence-ai-in-data-science-with-damodarrao-thakkalapelli-data-solutions-architect-556765
[30]. Talluri, Saritha, Venugopala Rao Randhi, Damodarrao Thakkalapelli, and Rama Venkata S. Kavali. "Multicomputer System with Machine Learning Engine for Query Optimization and Dynamic Data Reorganization." U.S. Patent Application 17/307,173, filed November 10, 2022.
[31]. Randhi, Venugopala Rao, Damodarrao Thakkalapelli, Rama Venkata S. Kavali, and Ravindra Dabbiru. "Correction, Synchronization, and Migration of Databases." U.S. Patent Application 17/830,849, filed September 22, 2022.
[32]. Kavali, Rama Venkata S., Lawrence D'silva, Venugopala Rao Randhi, and Damodarrao Thakkalapelli. "Electronic system for monitoring and automatically controlling batch processing." U.S. Patent Application 17/188,901, filed September 1, 2022.
[33]. Randhi, Venugopala Rao, Damodarrao Thakkalapelli, Rama Venkata S. Kavali, and Ravindra Dabbiru. "Correction, synchronization, and migration of databases." U.S. Patent 11,416,454, issued August 16, 2022.
[34]. Thakkalapelli, Damodarrao, Rama Venkata S. Kavali, Venugopala Rao Randhi, and Ravindra Dabbiru. "Correction, synchronization, and migration of databases." U.S. Patent 11,379,440, issued July 5, 2022.