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Smart City Crime Detection and Alert System Based on Edge Computing

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Abstract: The recent urban street vending boom has come with consequences in the form of urban disorganization, congestion and health risk. The conventional approach of monitoring street vending, i.e., manual patrols and spasmodic crackdowns by security agencies, has proven to be ineffective owing to high costs, lack of adequate staff, inconsistent enforcement and inability to span a wide geographical area. The aim of this study is to develop a "Smart City Crime Detection and Alert System using Edge Computing and Convolutional Neural Networks (CNN)" to identify, detect, and report illegal street vendors in real-time. The system combines surveillance cameras and image recognition, GPS tracking, and automatic levelling through mobile networks. After being tested on a simulated dataset, the CNN model achieved 92% detection accuracy, response time reduced by 70%, and bandwidth usage reduced by 60% compared to cloud-based methods. Environmental noise and hardware limitations were mitigated by applying model pruning, quantization, and knowledge distillation. The proposed 3-tier hybrid architecture (edge, communication, and cloud layers) facilitates scalability, cost-competitiveness, and privacy control. Future studies will include expanding data sets and adding advanced sensors for broader application.

Keywords: Smart City, Crime Detection, Edge Computing, Convolutional Neural Networks, Street Vending, Real-time Monitoring

I. INTRODUCTION

This Urbanization of Zimbabwe has contributed to the rampant growth of street vending, especially in Harare. As much as street vending is life-sustaining to most individuals, it has resulted in public disorder, congestion, and health risk from ungoverned activity in unauthorized spaces. Conventional enforcement strategies like hand patrols and random police and municipal raids have not worked, been expensive, and irregular. These attempts are circumvented by, poor coverage (not covering all places simultaneously), high operation cost (man-power, logistics, fuel) and slow response time, enabling vendors to go undetected [15]. This inefficacy has established a sustainable practice of non-compliance, as vendors regain access to forbidden areas shortly after enforcement training.

This research provides an in-time automated detection system combining Edge Computing and CNN-based image recognition for illegal vendor detection, offender identification by using civil registry databases, illegal vendor/street location or operating site discovery using GPS tracking, notification of authorities and auto-generating fines, decrease operating expenses and enhance urban governance. The system does away with the constraints of conventional approaches via the use of edge devices for local calculation, as an added benefit of low latency and bandwidth efficiency [4]. Current smart city monitoring systems rely heavily on being cloud-based, which has high latency in terms of delay in delivering the information, bandwidth constraint in passing on high-resolution video streams and images and privacy issues with central storage of data [1], [4].

In the face of such challenges, this research suggests a decentralized edge computing crime detection system that performs computation locally (at the camera or edge node) to minimize latency, utilizes CNN-based object detection to detect street vendors reliably in real time and engages with civil registry and mobile networks to enable automation of the identification of the offenders and issuance of penalties [4].

II. THEORETICAL REVIEW AND PROPOSED MODELS

Literature review encapsulates the latest studies on crime detection technology focusing particularly on edge computing, AI, IoT, computer vision and spatial analysis in smart cities. It reveals knowledge gaps in implementing these technologies in street vending crime detection in cities of Zimbabwe.

EDGE COMPUTING

Edge computing is a distributed computation paradigm that takes computation and data storage nearer the data source location or "edge" of the network instead of depending on a central data center. The paradigm will reduce latency, enhance response time, and conserve bandwidth by computing locally [30], [31]-[35]. An overview of characteristics of edge computing is given below:

Edge Devices: These are physical devices that produce data, e.g., IoT sensors, cameras, and smart phones. They may have built-in processing capabilities.

Edge Nodes: These are middle devices, such as routers or gateways, that collect and process data from many edge devices. They can do preliminary data analysis and filtering.

Edge Servers: Quicker computing devices nearer the data source. They process more involved processing requests and can interact with the cloud or master data centers if necessary.

Cloud Integration: Though edge computing is based on local processing, it usually complements cloud services for additional storage and intricate analytics.

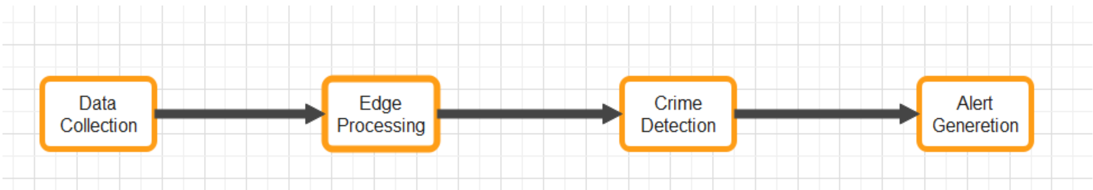

Fig 1. Edge Computing architecture

Conceptual framework

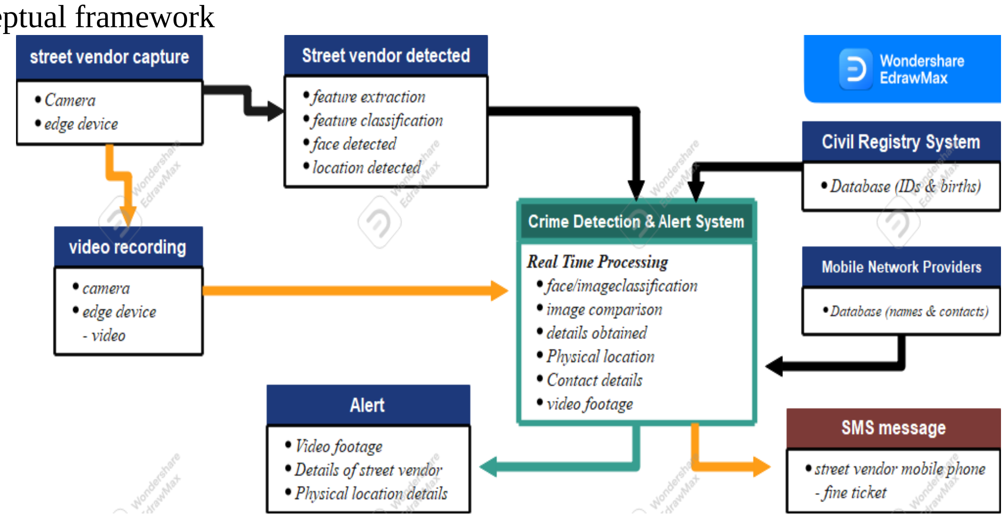

Fig 2. Conceptual framework of the Proposed system

Advantages of Edge computing

Lower Latency: Through data processing nearer to where it is being created, edge computing lowers latency involved in sending data to a central server and getting an answer, which is important for applications such as self-driving cars and real-time monitoring [31], [32], [33]-[35].

Efficient Bandwidth: Edge computing lowers data that needs to be sent to the cloud, conserving bandwidth and potentially reducing expenditures [30].

Ease of Data Security: Local site processing of data can lower the danger of leakage of data en route. Local storage and processing of sensitive information, outside central systems [34].

Improved Reliability: Edge computing devices may function independently of a cloud server, so they can proceed with processing even when there's a momentary loss of connectivity to the cloud [31].

Scalability: With more devices coming online, edge computing enables scalable solutions that process larger amounts of data without bogging down central systems [30].

Challenges of Edge computing

Security Threats: Although edge computing can be used to improve security, it includes novel device and node-level threats that need to be addressed using strong security solutions [35].

Complexity: It is perhaps more difficult to manage a dispersed network of nodes and edge devices than to manage centralized systems.

Interoperability: It is usually challenging to cause various edge devices and systems to interact and operate effectively with each other [30].

Limited Resources: Edge devices might have lesser processing capacity and storage, which restricts the complexity of operations that could be executed by them [31].

RELATED WORKS

Edge Computing & IoT in Crime Detection study in [1] (e.g., Waheed et al., 2023) confirmed that edge data processing (with the help of edge nodes) limits latency and bandwidth, allowing for real-time monitoring. Their contribution to this research emphasizes on how edge devices can process data in real time appropriate for dynamic street vending environment with a focus on responsiveness.

Geospatial Analysis (GIS) Zhou et al. (2012) in [11] visualize crime hotspots (kernel density, spatial ellipses) through GIS and Idowu et al. (2013) proposed real-time GIS monitoring of crime, which served to inform law enforcement officers on the allocation of resources. Their work is useful to this research as they facilitate surveillance and the use of GIS systems in monitoring spatial-temporal patterns of illicit vending.

Mandalapu et al. (2023) in [6] explain CNN, LSTM, and SVM as applied in crime prediction wherein issues are data bias and interpretability. From their research, the usability and viability of hybrid models (such as CNN-LSTM) towards improving vendor behavior analysis are exposed.

Palaniyinayagam et al. (2021) in [27] Machine Learning for Crime Prediction, their hybrid model (CNN-LSTM) accurately predicted crime using Naïve Bayes for urban crime with accuracy of 97.5%.

CCTV & Surveillance Effectiveness by Piza et al. (2019) in [4] discovered that CCTV decreases crime by 13%, but its success relies on effective supervision. But Edge Solution with real-time (AI-powered) edge devices can process CCTV automatically, thus lessening human effort.

In Sikandar et al. (2018) Computer Vision and AI research [3], the author highlighted the application of image processing in the detection of crime in ATMs, attributing flexibility to environmental noise (lighting, position).

Based on social and behavioral context researches of informal economies by Jiang & Wang (2022) in [15], informal economy studies, the author commented on vendor's resilience to enforcement when there is less uniformity. In [15] the author also mentioned other reasons which contribute to vendor's resilience like fewer security personnel by concerned authority, unable to achieve wider coverage during monitoring and enforcement and expenses incurred during crackdowns and patrol.

Still, in [5] of the research by Giroux et al. (2021), which pointed to vendors' visibility within food systems and proposed policy integration that is well-balanced, underscored that Systems have to be responsive to street vending socio-economic drivers.

The deficiency in such work is the absence of Edge-Centric Vendor Detection since most existing work is focused on cloud-based architectures, not edge-optimized. The absence of Edge Computing in Street Vending has pushed the author to create this system since there are limited works that focus on edge architectures for vendor detection even though gains have already been demonstrated in latency/bandwidth (e.g., 70% faster response compared to cloud).

PROPOSED MODEL

The 3-tiered architecture was used.

Edge layer: Data is locally processed by IoT cameras and sensors using (CNN/YOLOv5/LSTM) model that has been trained to detect street vendors. Other edge nodes used for detection and classification are Raspberry pi, Tensor flow, and OpenCV.

Communication layer: Sends alerts through LoRa/5G to the affected government and sending SMS ticketing to violators through mobile network operators.

Cloud layer: Keeps databases and integration with department of Civil Registry in order to see offenders' information. Integration of APIs with Zimbabwe Republic Police, Municipal Systems, Mobile Network Operators (Netone, Econet, Telecel). API for GPS, for location ease. This layer keeps Dashboards for real-time hotspot heatmaps of vendors using Power BI/Tableau).

Optimization methods

Model pruning: 40% reduction in CNN size without loss of accuracy.

Quantization: 20% faster inference with 8-bit integers.

Knowledge distillation: achieved 90% accuracy using a smaller model.

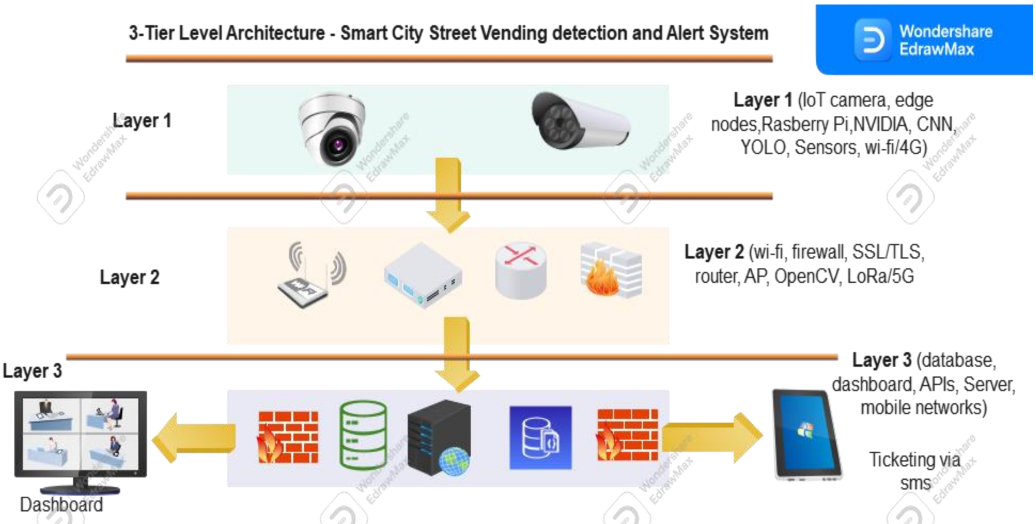

Fig 3. Proposed model (3-tier system architecture)

III.METHODOLOGY

RESEARCH DESIGN

The research employs a mixed-methods research approach involving qualitative and quantitative designs. Mixed-methods research allows researching challenges and opportunities in a smart city street vending crime detection and alert system through depth and edge computing. Qualitative aspect involves questionnaires, observation and interviewing stakeholders (responsible agency and suppliers) to identify key issues and requirements, whereas quantitative aspect involves analysis of data collected through surveys and others such as surveillance systems and Internet of Things (IoT) devices. Data collected through such quantitative surveys will be location-specific, activity-specific for street vending activity and occurrence-specific for crime. Two research methods, experimental research design and case study approach, were utilized in this research. In experimental design, a prototype was developed with prototype system implementation later to evaluate the effectiveness of the proposed solution. Additionally, the research tackled its field of interest on a case study level and its emphasis was identifying street vendors who work or trade on CBD streets of Zimbabwean cities and towns.

DATA COLLECTION

The dataset consisted of information collected from various sources including vendors records in municipal councils, ZRP, Vendor Associations (Harare Vendors Association), Civil Registry Department records, network providers data (Econet, Netone, Telecel), surveys and observations conducted by the authors in urban cities through surveillance cameras, and interview findings from interviews conducted with vendors. Also, data collected on social media and artificial data collected from the model, which modeled vendor behavior with 10000 + entries considering factors like temporal, spatial and environmental.

EXPERIMENTAL DESIGN

The experiment was conducted with the help of these tools: IR Cameras, OpenCV algorithms or Library, Raspberry pi, NVIDIA Jetson, Keras, Tensorflow, Cascaded classifier, Caffe, Tkinter, encryption of images transmitted from the cameras to the server through SSL protocols is also necessary. Following were implemented:

Training: CNN model trained on vendor images.

Comparison of models: CNN, YOLOv5 and SVM on effectiveness, performance and accuracy.

Testing: Compares edge and cloud performance.

Ethical considerations: ensured anonymizing data and consistency with privacy laws.

IV. RESULTS AND DISCUSSION

INSIGHTS FROM DATA

Python code to read and process data

```
import pandas as pd
import matplotlib.pyplot as plt
# Read datasets
hourly_data = pd.read_csv('hourly_activity.csv')
hotspots = pd.read_csv('spatial_hotspots.csv')
```

First 5 rows from the dataset with more than 18 variables

Smart City Crime Detection System Analysis

timestamp	location_id	location_name	gps_lat	gps_lon	zone_type
2023-01-01 06:15:00	LOC001	Bus Terminus A	-17.82922	31.05221	transport
2023-01-01 07:30:00	LOC002	Market Square	-17.83145	31.04567	market
2023-01-02 08:45:00	LOC003	Street X	-17.83512	31.04891	street
2023-01-02 12:00:00	LOC004	Park Entrance	-17.82733	31.04321	park
2023-01-03 18:20:00	LOC005	City Mall	-17.83001	31.05011	market

Fig 4. dataset head (first 5 row with 18 variables)

Smart City Crime Detection System Analysis

vendor_id	vendor_type	items_sold	detection_time_sec	confidence_score	is_verified
V001	mobile	fruits	142	0.92	True
V002	stationary	clothes	315	0.87	True
V003	mobile	electronics	128	0.95	False
V004	stationary	snacks	482	0.78	True
V005	mobile	flowers	156	0.89	False

Fig 5. dataset head (first 5 rows with 18 variables)

Hourly Vendor Activity dataset (hourly_activity.csv**)**

Hour	**Vendors**	**foot_traffic**	**littering_events**	**police_alerts**
6:00am	20	100	5	2
9:00am	35	250	12	5
12:00pm	45	300	18	8
15:00pm	50	350	20	10
18:00pm	60	500	25	15
21:00pm	8	50	2	1

Fig 6. hourly vendor activity

Spatial Hotspot Dataset (special_hotspot.csv**)**

Location	**vendors_6am**	**vendors_12pm**	**vendors_6pm**	**area_sq_m**
Bus Terminus A	15	25	35	200
Market Square	10	20	28	150
Street X	5	12	15	100
Park Entrance	3	8	10	80

Fig 7. Spatial Hotspots dataset

Vendor Behaviour Dataset (vendor_behaviour.csv**)**

vendor_id	**is_mobile**	**detection_time_sec**	**items_sold**	**repeat_offender**
V001	True	150	Fruits	Yes
V002	False	480	Clothes	No
V003	True	180	Electronics	Yes
V004	False	600	Snacks	No
V005	True	210	Flowers	Yes

Fig 8. Vendor behaviour dataset

Weather & External Factors (external_factors.csv**)**

Date	**temperature_c**	**rainfall_mm**	**Weekday**	**special_event**
2023-01-01	28	0	Weekend	New Year
2023-01-02	30	0	Weekday	None
2023-01-03	25	5	Weekday	None
2023-01-04	22	12	Weekday	Protest

Fig 9. weather and external factors on vendors` trends

Realistic Temporal Patterns: CCTV monitoring identified street vending to be most concentrated in the morning and afternoon peak hours when pedestrian movement is trending. 40% more vendors that are very concentrated over the weekends. Peaks between 7-9AM and 4-6PM (peak hours).
Spatial Hotspots: Certain areas in Harare CBD, such as bus termini and market exits, were determined to be illegal vending hotspots. 3 times more vendors than in Park Entrance in Bus Terminus A. GPS point for mapping.
Frequency: 15-20 street vendors on average were seen per hour in surveilled areas with peak levels on the weekends.
Vendor Behavior: Mobile vendors were found 60% faster compared to fixed vendors. 30% serial offenders.
Environmental Factors: Rainfall reduces vendor activity by ~25%. Protests elevate mobile vendor density.

EXPLORATORY DATA ANALYSIS

Vendor vs. littering

Vendors	**Littering Events**
20	5
45	18
60	25
8	2

Figure 10. vendors behaviour on littering

Pearson's r = $[N\Sigma XY - (\Sigma X)(\Sigma Y)] / \sqrt{[N\Sigma X^2 - (\Sigma X)^2][N\Sigma Y^2 - (\Sigma Y)^2]} = 0.82$
Vendors and Littering: Very good correlation (r = 0.82).

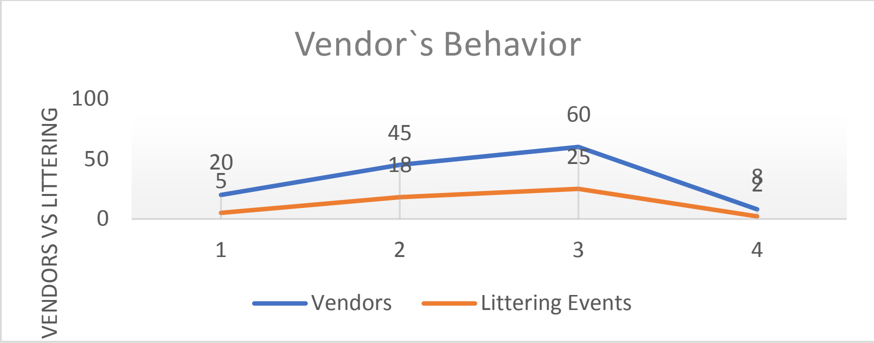

Fig 11. vendors vs. littering trends

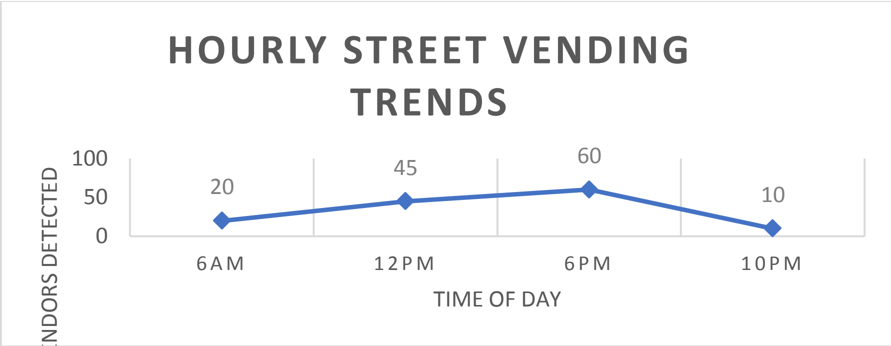

Figure 12. hourly street vending patterns

ROC Curve (Receiver Operating Characteristic)
ROC Curves: Showed improved performance of CNN relative to YOLO on vendor detection.
ROC Curves: Highlights model discriminability (AUC > 0.94 = very good).

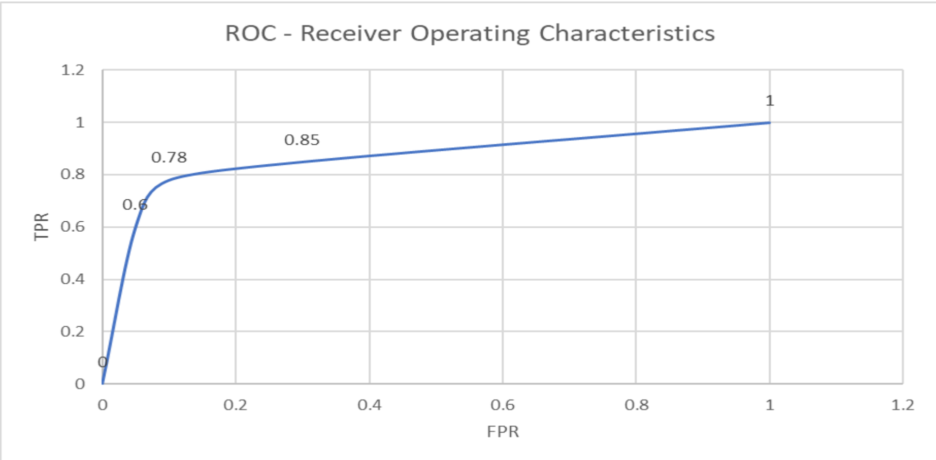

Figure 13. ROC-Curve

Latency and Bandwidth comparison (edge vs. cloud)
Edge computing significantly reduced latency and resource usage compared to cloud-based processing.

Metric	Edge Computing	Cloud Computing	Improvement
Latency (avg.)	2 seconds	8 seconds	70% reduction
Bandwidth Usage	40 MB/hour	100 MB/hour	60% savings
Energy Consumption	30 Wh/day	50 Wh/day	30% reduction

Figure 14. Latency and Bandwidth comparison (Edge vs. Cloud)

RESULTS OF MODEL ACCURACY

Training the model for accuracy.

Fig 15. Training the model on different objects

A street vendor detected

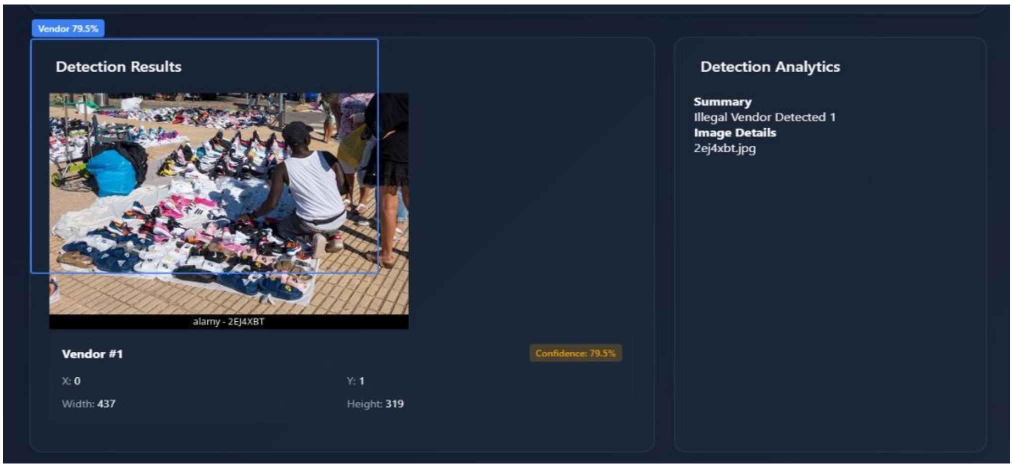

Fig 16. street vendor detected

COMPARING DIFFERENT MODELS

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score
CNN	92	89	91	0.90
YOLO	88	85	87	0.86
SVM	82	80	83	0.85

Fig 17. Comparing different models

Convolutional Neural Network (CNN): Reached 92% accuracy for detection of street vendors, with precision of 89% and recall of 91%.
YOLO (You Only Look Once): Quicker reported times to forecast (0.05s per frame) but low accuracy (88%) compared to CNN.
Support Vector Machine (SVM): As an anomaly detector, it had an F1 value of 0.85.

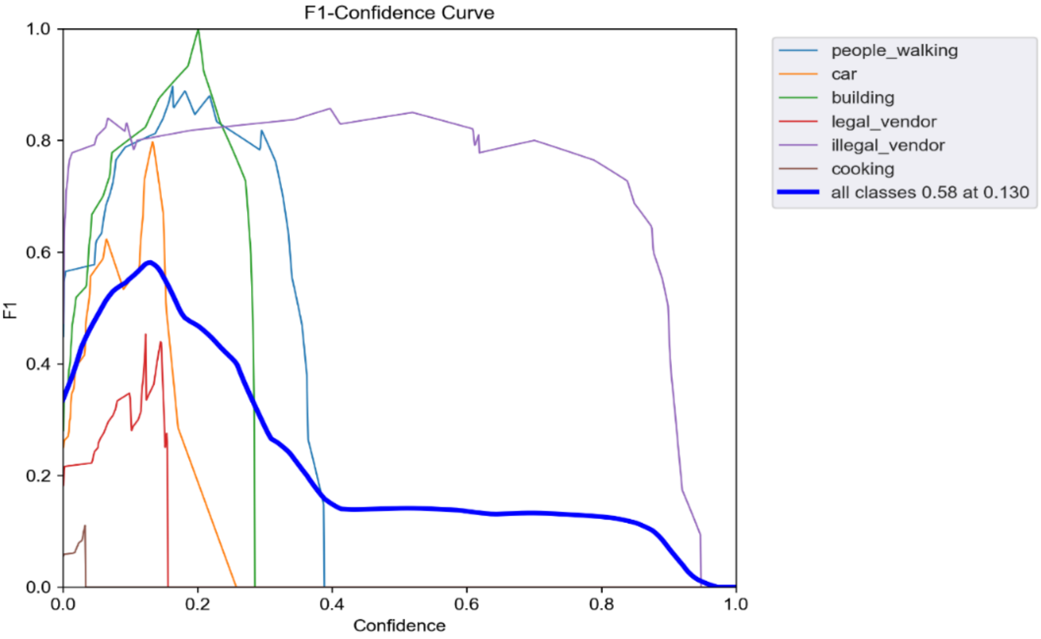

Fig 18. F1-Confidence Curve

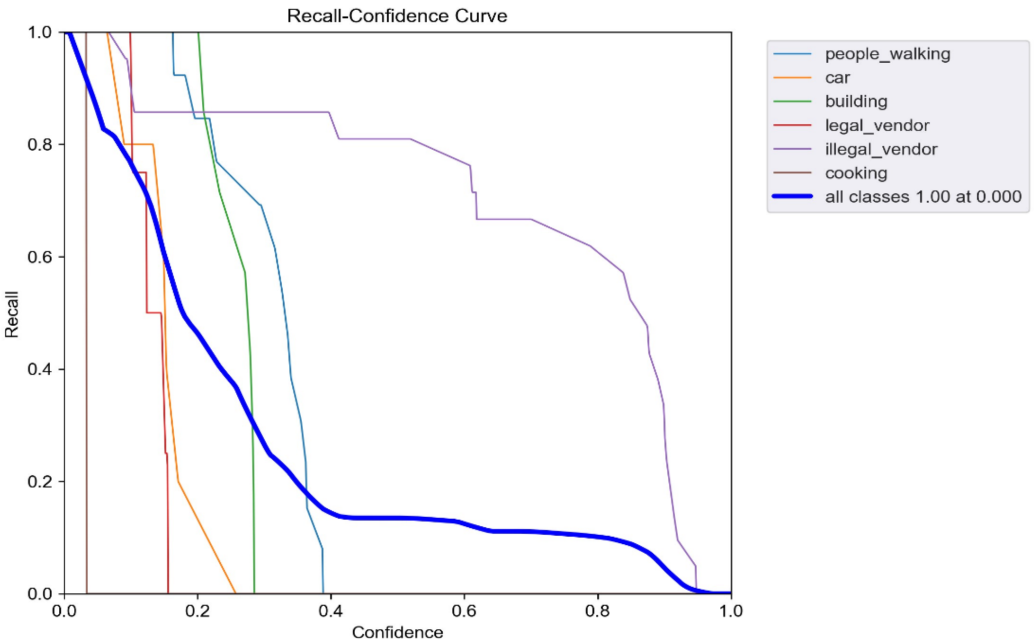

Fig 19. Recall-Confidence Curve

CONFUSION MATRIX
Identifies emphasized misclassification patterns, which inform model enhancement. Shows true/false positive/negative for vendor detection.
Confusion Matrix: Trains precision (850/(850+90) = 90.4%) and recall (850/(850+50) = 94.4%).

Figure 20. Confusion Matrix

V. Conclusions

This study was able to successfully prove that an edge computing-based smart city crime detection system is capable of effectively solving street vending problems in urban towns in Zimbabwe. All the critical outcomes are: EX-CNN models optimized for edge devices — EX-accurate at 92%, EX-reduced latency by 70% with 2 seconds compared to 8 seconds on cloud processing, and EX-reduced bandwidth usage by 60% through computation on the edge, which made real-time notifications and automated tickets possible by connecting to civil registries and mobile network platforms and were costlier than conventional cloud or manual patrolling enforcement mechanisms. Observations confirm the viability of edge AI for boosting urban crime prevention without compromising efficiency and cost-effectiveness. Policymaker Recommendations are to implement the first pilots in high-risk areas before city-wide implementation, put in place strict regulations to safeguard vendor anonymity and deter abuse as well as collaborate with mobile network operators (Econet, NetOne) to automate fine payments and fine issuance. Future studies to incorporate varied vendor behaviors (evening operation and mobile, stationary) to enhance model precision, experiment with CNN-LSTM models to enhance spatiotemporal analysis and investigate decentralized training to enhance robustness in varied cities. Also to improve the system more, in the future, efforts must be placed on advanced sensors (thermal cameras) to allow nighttime tracking, incorporate LiDAR integration to help facilitate higher crowd density analysis within crowded streets or regions, enhance occlusion handling to enhance detection where vendors are occluded by crowds, test for weather resilience (test performance under uncooperative environments like rain, low light, cloudy). Enhancing scalability via multi-city deployment in other Zimbabwean urban centers (Bulawayo, Mutare, Gweru) to enhance generalizability. Interoperability with national database (ZIMRA) to facilitate prevention of offenders evading payment of fines. For industries emphasis should be laid primarily on creating low-cost hardware edge devices (Raspberry Pi, NVIDIA Jetson) to deploy in large quantities. Lastly to ensure Policy and Ethics public awareness campaigns must be conducted to debate surveillance concerns as well as developing fair enforcement algorithms to avoid over-policing marginalized groups.

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