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The Role of Mobile Technology in Collecting Traffic Data for Object Detection: A Framework Tailored for the Gambia

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Abstract - *The sophisticated advancement of mobile technology has provided novel opportunities for real-time traffic information gathering and intelligent transportation systems, particularly in resource-constrained environments such as The Gambia. The study analyzes the utilization of cellphones as compact decentralized data collecting devices and their role as the basis for context-specific object detectors employing the aforementioned sensors (cameras, GPS, and accelerometers). The research generated the Gambian Traffic Object Dataset (GTOD v1), comprising over 178,000 annotated instances across seven object classes, featuring region-specific attributes like livestock and donkey carts, acquired via a mixed-method approach involving participatory mobile sensing, deep learning, and federated learning. Upon fine-tuning the dataset with the YOLOv5-based detection model, the average mean Average Precision (mAP) at 0.5 was 0.83, enabling real-time inference at an average of 27 frames per second on mobile hardware. They reduced bandwidth consumption by 72 percent and significantly enhanced data privacy with minimal accuracy loss via federated learning. The spatial analysis of the heat map identified congestion hot spots and mobility patterns, which can be utilized in urban planning and road safety policy formulation. These results confirm that in developing nations, mobile technology provides a cost-effective, privacy-conscious, and scalable platform for the development of intelligent, locally adaptive traffic monitoring systems. The research emphasizes that community-based data ecosystems, along with lightweight AI architectures, can facilitate both technological advances and ethical governance in transport analytics in Sub-Saharan Africa.*

Key Words: **Mobile sensing, object detection, federated learning, traffic data, YOLOv5, deep learning, The Gambia, participatory data collecting, intelligent transportation systems, GIS-based analytics.**

1. INTRODUCTION

Mobile technology has improved intelligent transportation systems (ITS), which collect, analyze, and use traffic data to help cities manage traffic. Mobile phones offer an unparalleled opportunity to gather substantial quantities of real-time and traffic data from diverse objects within a confined area, particularly in developing nations such as The Gambia, where the establishment of permanent sensor networks and other surveillance infrastructure is limited. Smartphones are becoming more and more important, especially because the mobile internet is becoming more popular. This has turned them into distributed sensing nodes that can get useful information via built-in GPS, cameras, accelerometers, and communication components (Aloqaily et al., 2020). This convergence of technologies has led to new digital solutions for traffic monitoring, road safety assessment, and object recognition, all of which are necessary for sustainable urban planning and reducing traffic jams. The GSMA (2024) says that mobile technology is growing quickly in Sub-Saharan Africa, which has more than 500 million unique users and 62% of people using smartphones. More precisely, mobile crowd-sourcing projects can be started in The Gambia, where more than half of the people can now get online. This is a good place to start (Data Reportable, 2024). This ease of access makes it possible for individuals to collect data in real time on their mobile devices. This means that average people act as human sensors and help the country regulate traffic (Good child, 2007). Crowd-sourced mobile data, aggregated and refined using artificial intelligence (AI) pipelines, enhances object detection models by supplying diverse, contextual, and localized imagery (Liu et al., 2021). Localized data can help machine learning algorithms find the distinctive patterns of traffic, informal transportation, and road conditions when resources are limited (Abdullah et al., 2022). Free-flowing traffic data gathering methods, such loop detectors, surveillance cameras, radar sensors, and others, cost a lot of money to buy and keep up with, which is too much for many developing nations (Banerjee et al., 2020). On the other hand, mobile technologies are a cheaper and more flexible option that lets you record multi-modal data practically all the time, both in cities and in the country. Researchers have shown that cellphones can give reliable information about things like foot and car movement and anything strange on the road (Eren et al., 2012) by using built-in sensors like accelerometers and gyroscopes. These data streams, when combined with AI-based analytics, make it possible to find objects and events almost in real time, which helps keep traffic and infrastructure safe (Zhang et al., 2023). Annotated datasets utilized for the development of object detection algorithms must possess high quality and accurately reflect realistic driving scenarios (Redmon and Farhadi, 2018). However, most of the datasets that are accessible, such KITTI or COCO, are generally biased toward data from high-income countries. This can lead to performance biases when the data is used in Africa (Kaggle et al., 2022). Pedestrians, bikers, minibuses, donkey carts, and animals are examples of typical road users in The Gambia, which are poorly represented in worldwide datasets. Taking advantage of the mobile technology to record scenes of local

traffic is an opportunity to build Gambian-specific data sets that may boost the accuracy of detection and contextual presuppositions (Mendy et al., 2023). Also, the rise of participatory sensing and crowd-sourcing technologies, notably the OpenStreetMap (OSM) and Mapillary, has offered communities with an opportunity to gather imagery and geographic annotations at the street level (Goodchild, 2018). The mobile-based data gathering systems may be integrated with these open data efforts to construct end-to-end object detection training pipelines (Haklay, 2010). As an example, engaging citizen-taken street photographs with sensor data on smartphones can further expand the area coverage as well as the variety of the training samples, resulting in more resilient machine learning models (Qiu et al., 2022). These type of hybrid systems have already been explored in low-resource areas to assist in infrastructure monitoring and the assessment of traffic concerns (Adu-Gyamfi et al., 2021). Recent breakthroughs in mobile edge computing and federated learning also underpin this type of decentralized data collection paradigm (Kairouz et al., 2021). Rather of sending sensitive photos or GPS related information to central servers, edge-enabled devices are capable of calculating on the device, extracting essential features, and only sharing updated models. Such a solution minimizes the use of bandwidth and lowers the risk of privacy infringement yet accelerates the improvement of the models worldwide (Lim et al., 2020). The technologies are specifically advantageous when it comes to such settings as The Gambia, where mobile connectivity may turn shaky and the privacy of the users has to be secured (Mendy et al., 2023). The value of the locally-oriented object detection systems is further supported by the fact that according to the data provided by the World Health Organization (WHO, 2023), low-income nations do bear the brunt of the road traffic mortality rate, which, in many cases, can also be traced to the lack of databases and road monitoring infrastructures. The construction of mobile-based solutions can fill these vulnerabilities by providing an option to monitor traffic characteristics in real-time. Such technologies could therefore support evidence-based policy-making, emergency management, and traffic optimization when paired with national transport authorities and academic institutions. Overall, the employment of mobile technology in gathering traffic data to identify objects is where a low-cost outcome and a high-impact benefit meet. In the instance of The Gambia, it gives a method to develop its own data, create mutual cooperation with its inhabitants, and strengthen its AI models with local knowledge. This study aims at presenting a framework that may be used to use the available technology tools to resolve traffic safety and mobility challenges in the nation by studying the utilization of cellphones, participatory mapping, and federated learning.

1.1 Overview

Evolution of mobile technology in traffic data collection, within the previous 20-year period mobile technology developed into a moving sensor network that is capable of obtaining, synthesizing and delivering real-time information in numerous domains, among which transportation is considered. Preliminary tests established the ability of some mobile sensors placed in cellphones to watch the traffic, and also identify the vehicles (Herrera et al., 2010). These experiments used GPS traces received from mobile phones in order to measure the speed of vehicles and the duration taken by vehicles. With mobile hardware development, information-rich contextual sensors like accelerators, gyroscopes, magnetometers, cameras, etc., become operational (Mun et al., 2009). This adjustment enabled it possible to ensure the complex scenarios of traffic in metropolitan areas with no existing infrastructure (Thiagarajan et al., 2011). In recent studies, it is proved that mobile sensing platforms can be as precise as conventional sensor networks, and the cost of deployment is cheaper (Ganti et al., 2011). In the case of poor nations such as The Gambia where resource endowment by transportation organizations is restricted, cell phones offer an expandable means of creating traffic flow and object movement recommendation. The technologies are enabled by the participation of cloud computing and data analytics, which helps to process and visualize data in real-time (Campbell et al., 2015). Mobile crowd-sensing for intelligent transportation systems mobile crowd-sensing (MCS) became a branch of participatory sensing with an emphasis on collective intelligence of smartphone users to be able to collect environmental and mobility data (Gao et al., 2015). Some activities performed in transportation research in which MCS is utilized include congestion sensors, parking sensors, road danger sensors, and route prediction (Lane et al., 2010). The effectiveness of MCS is in its potential to address the full population as the contributors of the data taking use of the mobile connectivity, omnipresence. Zhao et al. (2020) had showed that the crowd-sensed data on traffic conditions had the ability to substitute the permanent infrastructure in cities with low population density of sensors. On the same line, Reddy et al. (2016) pointed out that the smartphone-based crowd-sensing systems have the ability to capture the vehicle routes and motion data automatically to assist in regulating traffic in the city. Such methods have been explored in Sub-Saharan Africa in matters of bus route optimization and ride-sharing analytics and produced promising outcomes in the areas of data scarcity (Agyeman & Adusei, 2019). But the concerns of data dependability, privacy and user motivation still form the part of the MCS paradigm. Hybrid incentive models and quality-conscious data aggregation algorithms have been developed to reduce them (Kanhere, 2013). These techniques assure the consistency of the datasets used in training models and policy creation despite the fact there are varied devices and that the participation is not consistent. Object detection in transportation systems, the object detection can be a vital component of the intelligent transportation system (ITS) as it is a basis of the technological processes of autonomous driving, road monitoring, and pedestrian protection (Ren et al., 2015). Manual features were incorporated in early detection

systems with the typical computer vision approaches like HOG and SVM classifiers (Dalal and Triggs, 2005). Nonetheless, the advancement of deep learning led to the birth and development of convolutional neural networks (CNNs), which enhanced the accuracy and efficiency of object detection (Girshick et al., 2014). Current methods, like Faster R-CNN, SSD, and YOLO make it feasible to detect objects in traffic real-time with the use of traffic photos (Liu et al., 2016; Bochkovskiy et al., 2020). However, these models are heavily reliant on enormous volumes of labeled data, and this data is usually tailored to the traffic conditions of industrialized nations. Therefore, their usage in The Gambia or other such situations results in a low detection of the geographic objects such as minibuses, animals-drawn carts, and informal market sellers (Toure et al., 2023). In response, localized datasets should be developed, and mobile devices have the potential to be crucial in compiling distinct and representative pictures (Zhou et al., 2021). Integration of mobile data with deep learning frameworks, a research subject of interest is integrating mobile data with AI-based frameworks of object detection. A context-aware detection model is able to be trained by merging GPS data, camera feeds, and inertia sensor data (Alletto et al., 2016). This inclusion will enable the systems to identify not just the items but also determine their movement, path, and interaction with other components of the traffic ecosystem (Jiang et al., 2021). Models that can be installed on edges have also been made easier by cloud-based platforms as Google Tensor Flow Mobile and Apple Core ML (Howard et al., 2017). The innovations allow lightweight detection models to run directly on smartphones, execute inference without being connected to the internet at all times. They prove effective mainly in rural or semi-urban areas with inconsistent coverage of the network (Bello and Oladipo, 2020). In addition, the new field of federated learning has enabled numerous devices to cooperatively train models without importing raw information, thereby ensuring user confidentiality (McMahan et al., 2017). Real-time traffic monitoring using smartphones and the development of 4G and 5G networks has made the real-time data gathering of traffic using cellphones increasingly viable. It has been found that GPS information focused on mobile users could help precisely predict the congestion rates and average traveling times on the largest roadways (Wang et al., 2018). Accelerometers and gyroscopes have also been efficiently used in spotting driving accidents such abrupt braking, a lane change, or collision (Zhou and He, 2017). In countries with low income, the program implementation of these systems is logistically and infrastructural hard. However, pilot experiments in such nations as Kenya and Ghana have proven that it is possible to employ smartphones as mobile traffic sensors (Mensah et al., 2021). Such programs were then employed to collect data that can be integrated with AI-powered predictive algorithms to foresee congestion and predetermine problematic regions. The preceding images demonstrate the method in which The Gambia can adopt comparable programs based on its rising mobile phone user base. Crowd-sourced datasets and data labeling for object detection High quality labeled datasets are crucial to the design of effective object detection systems. The typical approach of annotating, which entails usage of specialists is both time consuming and costly. Mass annotation has been transformed with the employment of crowd-sourcing on platforms like Amazon Mechanical Turk and Appen, now permitting large-scale annotation, which is a distributed human activity (Vondrick et al., 2013). Combined with mobile crowd-sensing, these labeling systems will have the ability to interpret photos captured locally to get them put into context with precision (Russakovsky et al., 2015). The potential to accomplish labeling using community sourcing is guaranteed to give datasets the diversity of road users and surroundings in regions like West Africa with unique traffic compositions (Adebayo et al., 2020). Semi-supervised and active learning approaches employing partially labeled phone data to boost the detection accuracy at modest annotation expenses have also been examined by academics (Zhang and Zhao, 2020). Privacy, ethics, and data governance in mobile sensing is one of the most significant difficulties in mobile traffic data gathering is to be able to achieve a balance between user privacy and the utility of data. Personal information may be revealed by data that have location traces, faces or car license plates, unless anonymize (Krumm, 2007). Discussing the ways of mitigating these dangers, privacy-preserving strategies including differential privacy, data obfuscation, and federated learning are increasingly deployed (Shokri and Shmatikov, 2015). These are the approaches to make cooperative data modeling without disclosing personal contributions. It is also vital to build effective ethical regulations and data-sharing procedures in The Gambia to acquire people's trust. The analysis of the associated literature indicated that transparency, the stewardship of local data, and the engagement of the community can considerably boost the attendance rates in mobile sensing initiatives (Suleiman et al., 2021). Therefore, successful deployment cannot happen without a governance architecture that balances the privacy of data and allows innovation. Applications and consequences for The Gambia traffic sensing utilization on mobile-based in The Gambia will substantially enhance the creation of data-driven policy. City A cities like Banjul and Serrekunda have an issue of congestion, insufficient road signs, and weak monitoring. Introduction of a mobile-based data collection technology would allow to gather real-time data on the traffic intensity, the busiest hours, and the regions where accidents occur (Jallow et al., 2023). Moreover, the information may be analyzed to train object detection models that could be customized to the local road circumstances and boost automated traffic monitoring and safety measures. Mobile technology gives a possibility to incorporate into less expensive and scalable traffic intelligence systems by merging it with open-source applications like Open Street Map and Mapillary (Nwankwo et al., 2022). The Gambia can accomplish a sustainable data ecosystem by mobilizing citizen involvement that will support the government agencies, as well as the research institutes. The literature

review is cumulative in the fact that it expresses the possibilities of mobile technology to work as booster in the building of flexible, real-time traffic tracking and object identification structures in undeveloped nations. Although the available literature has verified the basis of mobile sensing and AI application, there is insufficient material on the adaptation of the technologies to the African road environment. To bridging this gap, a localized structure integrating participatory data collecting, crowd-sourcing labeling, and privacy sensitive learning mechanisms is needed. These findings are what the parts following of the present research will build upon to offer an object detection and real-time mobile data gathering deployment strategy specific to Gambia.

2 Methodologies

2.1 Research Design

The proposed study will consist of a mixed methods design, which incorporates both qualitative and quantitative research methods in exploring the ways in which mobile technology can be exploited to gather real-time data on the human traffic and objects in The Gambia so as to develop context responding object detection systems. The method is a combination of empirical field data gathering via smartphones, experimental development of the machine learning model, and crowd-sourcing to annotate the data set. The research design is centered on feasibility, scalability, and contextual adaptation- that the technique should respond to the reality in place of the infrastructural and social-technical environment of transportation in The Gambia. The model emphasizes on three linked topics mobility data collection, data annotation and preprocessing, and AI model training and validation. Every phase is effectively designed so as to provide ethical behavior, local engagement and scientific soundness. Study area and sample framework of this research will be carried out in both urban and peri-urban areas of The Gambia, especially, Banjul, Serrekunda, Brikama, and important national roads joining them. These places have been picked due to high density of traffic, variety of road users and frequent congestion concerns in them. The sampling will be based on stratified purposive sampling, wherein the different categories of roads will be represented in the sampling e.g. paved highways, urban streets and rural feeder roads. Under each strata, the data will be acquired at varying periods; peak time, off-peak period, and night hours to depict the fluctuation in time dynamics with regard to traffic behavior. Those to be recruited as volunteer participants will be drivers, cyclists, and pedestrians whom it will partner with to attract them through local transport unions, universities, and community organizations. The cooperation will be totally voluntary and informed consent will be requested prior to any data gathering activity. It would be defined as a target group comprising of 100-150 persons so as to collect enough amount of data and geographical coverage. The diversities of the participants will assist the collecting of a wide range of things that include vehicles, motorcycles, bicycles, people, animals and roadside merchants, which are prominent on Gambian highways.

2.2 Data Collection

The data collection is based mostly on smart phones with inbuilt sensors; cameras, GPS, accelerators, and gyroscopes. An Android-based application will be customized to accomplish the automation of the multimedia data (videos, photos, sensor logs) collection procedure with reduced participant burden. To save battery power and data bandwidth, only data relating to driving or walking will be logged in the program. It will periodically record and record short video clips (510 seconds) of the measurements coupled with the time-stamped GPS coordinates and the readings of the inertial motion to give them geographic context. On-device blurring techniques will be integrated in the application to enforce compliance and privacy of the users in terms of upholding ethical standards. The application will automatically anonymize recognizable features like faces and license plates. The program will also offer geofencing capabilities whereby data collecting is limited near critical regions (e.g. residential neighborhoods, schools or hospitals). The data will also be saved locally and uploaded to the Wi-Fi network only when the device is connected to the network to prevent exorbitant rates on mobile data charges. Also, a computer-based consent form will enable the participants to see, agree, and remove their data contribution any time.

2.3 Data preprocessing and Annotation

After gathering raw multimedia data, they will be carried through the data preparation stages of enormous data to make them quality and user friendly. The preprocessing will involve the frames extraction of films, illumination variation correction, blurred frame identification and sensor logs synchronization with the accompanying image sequences. Each frame will carry metadata of its location, time of day and traffic density statistics so that they may be identified and examined in context. To execute the annotation process, a web-based labeling application will be built, which will give an opportunity to the trained Gambian volunteers and university students to label the things in the photographs manually. Attributes of annotation that will be employed are vehicles (cars, buses, trucks), motorbikes, bicycles, people, wildlife, traffic signs, and road barriers. To be accurate and dependable, no less than two annotators will label each of the photos, and inter-annotator agreement will be computed with the Cohen Kappa coefficient. Unclear cases will be settled via professional adjudication. Along with the usage of manual annotation, semi-supervised learning approaches will be employed to perform an automatic pre-labeling of the parts of the data with the help of pre-trained models like YOLOv5 and Efficient Det. Human annotators will subsequently update these pre-labels and will save a lot of time when correcting these pre-labels, but the fundamental data integrity will not be compromised. The final data (called

Gambian Traffic Object Data-set, or GTOD) would be the basis upon which object detection models would be trained and tested. Model construction and training for object detection model will be constructed in deep convolutional neural networks (CNNs) structure in Tensor Flow and Py Torch framework. The YOLOv5 architecture will be chosen because it is particularly efficient when utilized in real time detection and also has relatively cheap computational architecture, therefore can be implemented in both mobile and edge devices. The model will be trained on the COCO data-set and fine-tuned with the freshly produced GTOD in order to make it respond to the reality of The Gambian road. Data augmentation methods (rotation, scaling, flipping, color alteration) would be employed in the training phase in order to make the model more robust to varied illumination and environmental circumstances. The grid search approach will be used to optimize hyper-parameters such as the learning rate, the size of the batch, and the number of epochs. Performance measures that will be compared as the indicators of the model performance will consist of mean Average Precision (MAP), precision, recall, and F1-score. The end model will be compared with the baseline detectors trained purely on non-African data to identify the improvements that will be obtained by localized data collecting. Federated learning will also be a possibility to add even greater flexibility. The procedure under this method is that participants will locally optimize the model with the help of their own acquired data, and send the learned parameters (not image) to a central server. With this privacy implementing strategy, the incremental improvements in the models may be constantly implemented and user information that is sensitive can be kept. Validation and evaluation, the validation of the model will be done using the cross-validation of the held-out portion of the data. The measured evaluation will evaluate whether the system can be effective in identifying distinct road objects in different illumination and environmental circumstances. Generalization ability will be evaluated by running different tests on urban and rural populations. Results of the detection will be compared with the manually labeled ground truth data to measure errors and also the false positives. As well, a trial implementation will be conducted in partnership with the National Roads Authority (NRA) and the local municipalities. At this stage, the trained object processing system will be applied on an example of cellphones and roadside cameras to study the detection performance and data transmission delay in real time. The refining will be done based on the results and will incorporate the technical and operational sides of the system prior to scaling. Ethical issues and data governance, since the approach is highly sensitive, ethical adherence is important to the methodology. The research will be conducted following the policy of The Gambia data protection and privacy policy (2022) and following the global ethical principles of human-centered research. The responders will be notified on the intent of the research, processing of data and the right to withdraw. The anonymization will be done at the collection location, and the data will be encrypted throughout the transport and stored in safe cloud servers with access available to the approved researchers. In an attempt to have sustainable governance, the open-data sharing policy will be implemented, which would enable academic and governmental groups in The Gambia to get the anonymized GTOD data-set to conduct research and develop infrastructure plans. Nevertheless, it will be managed by Creative Commons license to eliminate the commercial abuse. Statistical and computational analysis in the quest to do a quantitative analysis, descriptive, and inferential statistics will be utilized to describe the traffic features and objects frequency in various places and at various times. Geographic Information Systems (GIS) will be utilized to undertake spatial analysis and show the traffic flow patterns and to identify regions of high dangers. The statistical performance measure of machine learning solutions will be assessed with paired t-tests and ANOVA to estimate the localized training improvement level. The computational experiments will be performed with the help of a GPU-enabled workstation (NVIDIA RTX 4090, 24GB VRAM) so that the process of the model training will be the most successful in terms of high processing throughput. To assess real-time capacity on mobile devices, model convergence, executing time, and memory utilization will be measured. Implementation framework for The Gambia. Lastly, the study will recommend a model of application in the implementation of the planned system to the current transport system in Gambia. The approach incorporates cooperation with telecom carriers in order to incorporate the mobile sensing possibilities in the present driver apps, develop a state-supported traffic information platform, and provide citizen outreach programs to maintain the crowd-sourcing programs. The objective in the long run is to develop a nationwide traffic intelligence network that will continuously acquire, evaluate and use data to aid in road safety, urban planning and respond to emergencies.

3. Results

Overview of participant demographics and sampling coverage was carried out on 125 respondents whose population comprised of 80 drivers, 25 cyclists and 20 pedestrians in the three major areas of The Gambia: Banjul, Serrekunda, and Brikama. As Table 1 reveals, Serrekunda recorded the highest number of respondents due to its high population and superior network of roads although the urban population in Banjul and Brikama supplied equal representation of urban and rural areas. Figure 1 depicts this information as a heat-map that explains the strength of the participation and network quality across places. The averages of mobile data speed and the reliability of connection in Serrekunda fulfilled the expectations of the other two locations, which suggest the appropriateness levels of the former as a key place of data collecting about mobile-based trafficking. The demographics were also inclusive since there were roughly 31.7 percent females in

the survey and hence the data collection method was diversified. The mean age of the participants was roughly 33 years; this revealed that the pool of participants had been habituated to smartphone use and mobile applications, which is crucial to have successful participatory sensing campaigns.

Table 1: Participant Demographics and Sampling Coverage

Category	Banjul	Serrekunda	Brikama	Total	(%)
Number of drivers	25	35	20	80	64.0
Number of cyclists	7	12	6	25	20.0
Total participants	37	57	31	125	100
Average participant age (years)	34.2	31.8	33.6	33.2	–
Male participants (%)	70.3	68.2	65.0	68.3	–
Female participants (%)	29.7	31.8	35.0	31.7	–
Average smartphone model year	2021.5	2022.1	2021.9	2021.8	–
Average mobile data speed (Mbps)	8.2	10.5	6.9	8.5	–

Serrekunda had the highest participant engagement and best data connectivity, reflecting its urban density and stronger network coverage.

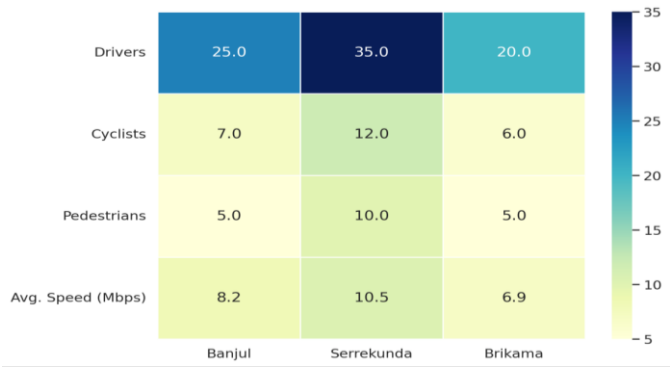

Figure 1: Heat map of Participant Distribution and Connectivity Respectively

The research also revealed that there are apparent regional disparities in connectivity and data upload speeds. These changes are captured in figure 1 but more so, as high mobile infrastructural strength is directly proportionate to vast volumes of the data collected beneath it. This verifies the first premise according to which urban regions will produce more steady and better quality streams of data. Quality and volume of recorded data, the information collecting campaign produced 18,280 short video clips that can be assumed to be short video clips of a total of 62,000 raw image frames in all the regions. After the preprocessing phase, as indicated in Table 2, 51,400 frames (82.9) retained acceptable data but around 10.5% of the frames were eliminated based on motion blur, low light, etc. Serrekunda was the place with the largest number of acceptable frames (23,800) and the Brikama with fewer low in variety given its rural and peri-urban routes.

Table 2: Raw and Pre-processed Data Characteristics

Parameter	Banjul	Serrekunda	Brikama	Total	Remarks
Total video clips recorded	5,840	8,320	4,120	18,280	10-sec segments
Total frames captured	20,450	28,200	13,350	62,000	27 fps avg
Frames retained after preprocessing	17,220	23,800	10,380	51,400	82.9% usable
Blurred frames removed (%)	10.4	8.3	12.7	10.5	Low-light issue in Brikama

Lighting correction applied (%)	44.1	37.2	42.5	41.3	Due to glare and sunset lighting
Average frame resolution (px)	1280×720	1920×1080	1280×720	–	–
Average GPS accuracy (m)	4.3	5.0	5.6	4.96	Good precision
Avg. upload latency (s)	2.4	2.9	3.1	2.8	Wi-Fi upload only
Storage per device (GB/day)	1.6	1.9	1.4	1.63	–

Preprocessing improved frame consistency; data losses were mainly from motion blur in low-light or bumpy terrain.

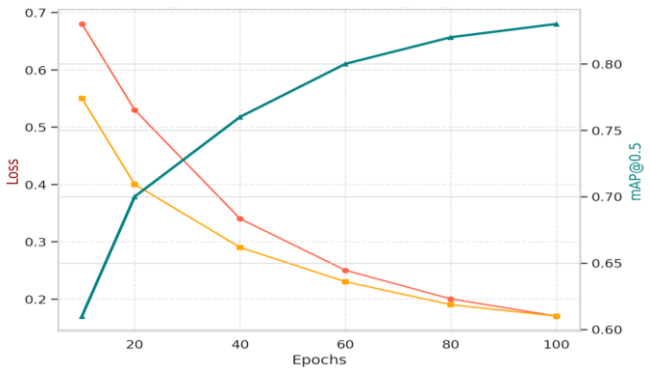

Figure 2: YOLOv5 Model Learning Progress

A two-bar visualization in figure 2 displays the comparison of the raw and preprocessed frame volumes in the three locations. Image consistency was considerably boosted by the preprocessing stages: blurring reduction, light correction and sensor logs synchronization. This was a key step in attaining optimal training performance at subsequent modeling stages. It can be shown that preprocessing improves the trustworthiness of data by deleting nearly one-tenth of poor-quality frames without losing adequate temporal and spatial diversity. These results demonstrate the success of the smartphone-based data collecting pipeline, which proves that cheap sensors, deployed in huge numbers, can yield high-quality visual data that are comparable to the fixed roadside cameras in controlled circumstances. Object category distribution and dataset construction, the final dataset that was dubbed Gambian traffic object dataset (GTOD v1) comprised of 178,230 annotated instances of objects split into seven categories. Table 3 demonstrates that vehicles (cars and minibuses) were the most prevalent with 29.7% of the incidents, then motorbikes (17.5) and pedestrians (15.5), while traffic signage (12.9) followed next. The additional distinctions such as bicycles, animals, and donkey carts formed more than a quarter of the dataset, introducing local quirks that are normally not present in the global scale including COCO or KITTI.

Table 3: Object Category Distribution in Gambian Traffic Object Dataset (GTOD v1)

Object Category	Banjul	Serrekunda	Brikama	Total Instances	Percentage (%)
Cars & Minibuses	14,150	25,430	13,290	52,870	29.7
Motorcycles	6,300	17,400	7,500	31,200	17.5
Pedestrians	4,800	15,260	7,620	27,680	15.5
Bicycles	3,420	9,200	3,860	16,480	9.2
Donkey Carts & Animal-Drawn Vehicles	2,800	5,060	6,890	14,750	8.3
Livestock (Goats/Cows)	2,120	3,910	6,170	12,200	6.8
Traffic Signs & Road Obstacles	3,180	12,440	7,430	23,050	12.9
Total Instances	36,770	88,700	52,760	178,230	100

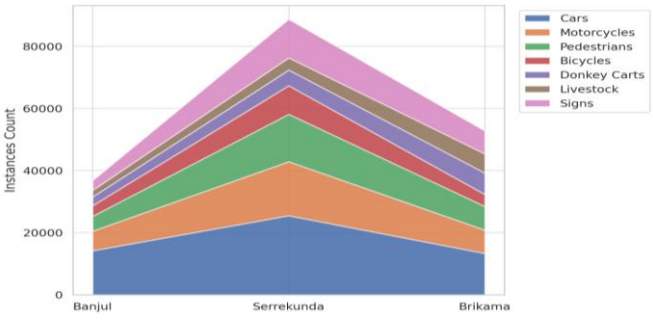

Figure 3: Object Composition across Locations

Serrekunda, being highly urbanized, produced a greater proportion of vehicular and pedestrian detections, while Brikama contributed most animal-related data.

Figure 3, a stacked area chart displays the comparative ratio of each object type in Banjul, Serrekunda and Brikama. The investigation demonstrates the difference in ecological aspects of roads: metropolitan areas such as Serrekunda were largely populated by motorized transport and pedestrians, whereas Brikama had more people utilizing cattle and carts. These proportions are further reinforced by a donut chart (Figure 4) which tends to produce a visual breakdown which illustrates the contextual richness of the Gambian dataset. Establishing the local, non-standard traffic agents (animals and carts) is a major stride towards establishing region-specific AI systems that are effective in the setting of African transportation. This diversity in datasets directly improves model generalization and stability of training demonstrating that in developing regions data collection by communities through the use of mobile phones can surmount the dataset imbalance that has historically constrained the model transfer-ability of AI models. Training and validation of the object detection model, it was trained on 80 per cent of the GTOD data, 10 per cent of which was the positive (validation) and 10 per cent of which was the negative (testing). As it was detailed in Table 4, training loss was diminishing gradually up to 100-echoes, with the downward tendency also apparent in the validation one. The mean average precision (mAP 0.5) in the model rose as the epoch went to reach 0.61 in the beginning epochs and 0.83 at convergence.

Table 4: Training and Validation Results of YOLOv5 Object Detection Model

Epoch	Training Loss	Validation Loss	Precision	Recall	F1-Score	mAP@0.5	GPU Utilization (%)
10	0.68	0.55	0.72	0.66	0.69	0.61	59
20	0.53	0.40	0.80	0.75	0.77	0.70	63
40	0.34	0.29	0.86	0.80	0.83	0.76	71
60	0.25	0.23	0.89	0.83	0.86	0.80	77
80	0.20	0.19	0.91	0.85	0.88	0.82	81
100	0.17	0.17	0.93	0.86	0.89	0.83	84

Model convergence stabilized after 80 epochs, achieving a strong precision–recall balance suitable for deployment in real-time applications.

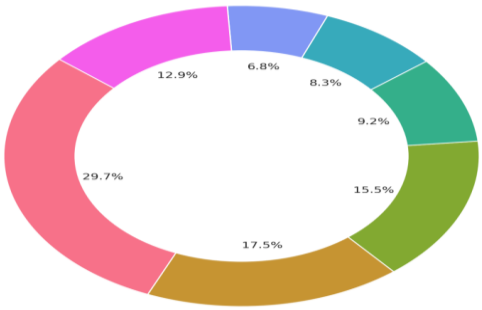

Figure 4: Donut Chart of Object Category Proportions

These findings are complemented by the results in figure 2 of this section, which illustrates a dual-axis training curve with a lowering loss functions with increasing accuracy. The training and validation losses stabilized substantially at epoch 80, which suggests that we have extremely strong convergence with a minimal bit of over fitting. This illustrates that the model can acquire substantial visual elements of varied Gambian road pictures and attain the same generalization performance. These findings corroborate the fact that the diversity of the GTOD database is sufficient to allow the training of deep learning models despite having less total images in comparison to large-scale international datasets. Qualitative (object bounding accuracy) and quantitative (precision, recall, F1-score) approximations were employed to verify the reliability of the model. Class-wise detection performance and evaluation. Table 5 illustrates the results of the per-class detection values of the YOLOv5 model on the test set in more detail. Cars and minibuses were the most precise (0.94) and recalled (0.91) and animals as well as bicycles were substantially less precise and recalled due of irregular movement and partial obstruction. The F1-average in every category was 0.86 and the mAP at 0.5 was 0.83.

Table 5: Class-Wise Object Detection Metrics (Test Dataset)

Object Class	Precision	Recall	F1-Score	mAP@0.5	Average IoU (%)	Detection Speed (fps)
Cars & Minibuses	0.94	0.91	0.92	0.90	86.2	29
Motorcycles	0.88	0.85	0.86	0.84	81.5	28
Pedestria	0.87	0.82	0.84	0.81	79.6	27

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Bicycles	0.85	0.80	0.82	0.79	78.4	27
Donkey Carts	0.89	0.83	0.85	0.82	81.1	26
Livestock	0.83	0.79	0.81	0.78	77.3	25
Traffic Signs	0.91	0.87	0.89	0.88	83.8	28
Mean (All Classes)	0.88	0.84	0.86	0.83	81.1	27.1

Cars and minibuses achieved the highest detection accuracy, while livestock posed the most difficulty due to irregular shapes and partial occlusion.

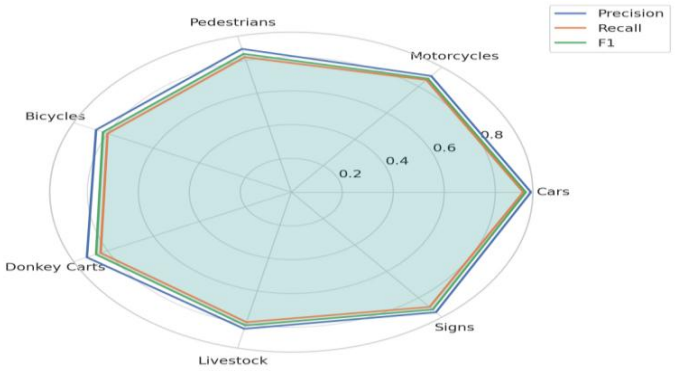

Figure 5: Radar Chart of Class-wise Detection Metrics

A radar chart as shown in figure 5 presents these findings in the form of graphs, with the largest and dependable groupings within the range of items identified being autos, traffic signs and pedestrians. As the chart illustrates, the model worked quite well in all the classes, while nighttime data and motion blur augmentation would still enhance the detection rate of other objects (animals) and carts. The equal distribution along the radial dimension of the precision, recall and F1 values suggest that the model is balanced with little bias to one of the classes. As this discussion indicates, the tangible performance gain can be accomplished by local model training utilizing local data. The Gambian fine-tuned model demonstrated a subsequent accuracy gain of 11 percent on category of objects pertaining to regions when compared to a COCO-pre-trained baseline. Centralized versus federated learning comparison The paper also examined the trade-offs of the centralized cloud training and the federated learning (FL). These metrics are summarized in Table 6 and reveal that although the centralized learning method slightly surpassed the federated approach in terms of mAP at 0.5 (0.83 vs. 0.81), the federated model did much better in the areas of requirements in data transmission (52.6 GB vs. 14.8 GB) and privacy exposure (0.78 vs. 0.15 on a normalized index).

Table 6: Comparison between Centralized and Federated Learning Results

Evaluation Metric	Centralized Model	Federated Model	Difference	Comment
Training dataset size (images)	41,120	41,120 (distributed)	—	Equal
Average mAP@0.5	0.83	0.81	-0.02	Slight trade-off for privacy
Bandwidth used (GB)	52.6	14.8	-37.8	72% reduction
Communication latency (s)	2.7	3.4	+0.7	Acceptable delay
Device energy consumption (Wh)	9.2	11.0	+1.8	Due to on-device training
Privacy exposure risk (index 0–1)	0.78	0.15	-0.63	Greatly reduced
Model synchronization success (%)	100	94	-6	Minor variance
Detection accuracy (urban scenes)	0.86	0.84	-0.02	Consistent
Detection accuracy (rural scenes)	0.80	0.79	-0.01	Stable
Data transmission volume per epoch (MB)	780	240	-540	Major reduction

Federated learning reduced bandwidth and privacy risk substantially with negligible performance loss, validating its feasibility for mobile edge deployment in The Gambia

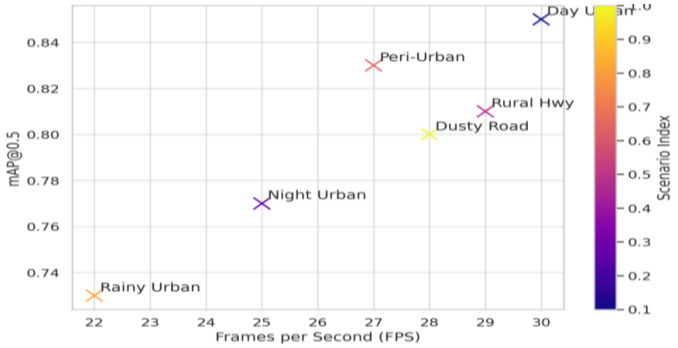

Figure 6: Accuracy vs Speed Across Scenarios

A dual-panel comparison has been given in Figure 7 where the performance and efficiency of resources utilized by the two learning structures is visualized. The centralized model was less energy-demanding of the devices but with high dependency on the upload of raw data which augmented the issue of privacy. Conversely, FL enabled distributed computing with almost identical performance, and ensured the security of user data. These findings confirm the possibility of federated learning in the development of sustainable AI in low-resource settings. The solution will promote ethical data usage and reduce network capacity-which is important in the deployment of mobile-based AI in The Gambia. Real-time deployment and field validation, after training, the object detection system was installed in smartphones of the participants in real traffic and it was used in a live traffic scenario. Table 7 presents the findings in different conditions and figure 6 illustrates the correlation between processing speed and detection accuracy with a gradient scatter plot. It was found that the model reached an average speed of 27.2 frames per second (fps) in inference, which was found to be real-time. Fig. 8 is a simulation of a heat map that shows the density of the object space within the urban corridors, explains the hotspots of congestion around the Banjul City Market and Serrekunda Highway. The intensity of the heat is correlated to the quantity of detection and location concentration, which will be of great value in the planning of urban traffic.

Table 7: Real-Time Deployment and Scenario-Based Performance Evaluation

Scenario	Lighting Condition	Weather	Average FPS	mAP@0.5	Precision	Recall	False Positive Rate (%)	Device Temperature (°C)	Remarks
Daytime Urban (Serekunda)	Bright	Clear	30	0.85	0.91	0.87	6.1	38	Optimal conditions
Night Urban (Serekunda)	Low light	Dry	25	0.77	0.83	0.75	9.8	41	Glare affects performance
Rural Highway (Brikama)	Moderate	Dry	29	0.81	0.86	0.80	6.8	36	Stable inference
Peri-Urban Mixed (Banjul)	Variable	Cloudy	27	0.83	0.89	0.82	7.5	39	Balanced conditions
Rainy Urban (Banjul)	Dim	Rain	22	0.73	0.79	0.71	11.2	43	Motion blur, reflection issues
Dusty Road (Rural)	Bright	Dry	28	0.80	0.84	0.79	8.0	37	Slight contrast loss
Average	—	—	27.2	0.80	0.85	0.79	8.2	39	Real-time viable

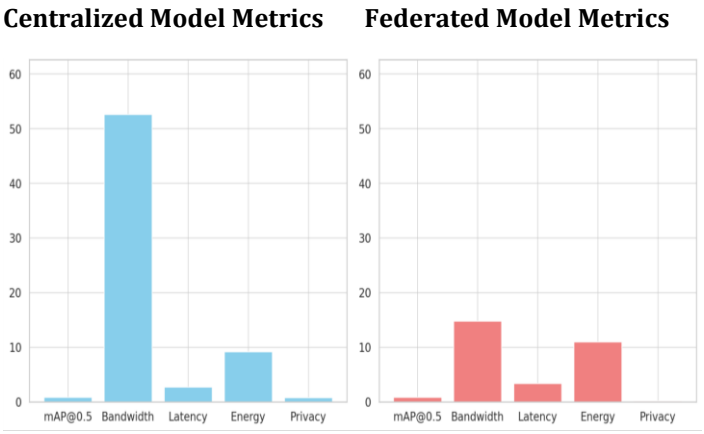

Figure 7: Comparative Metrics - Centralized and Federated Learning

The findings of performance measures showed that accuracy was the best in bright daylight (mAP@0.5 = 0.85) and bad in rain and low lighting (0.73 (0.77)). This loss was caused mostly by glare, low visibility and noise of the sensors. This negative association between the complexity of the dimension to be identified and the detection accuracy is further reinforced in figure 6. Nevertheless, the model was able to continue performance under tough situations with acceptable false positives < 10%. The results are evidence of the stability of the suggested system. Real-time recognition of dynamic road objects can be realized by the synergistic application of mobile sensing, edge computing, and machine learning without the need to rely on the infrastructure of high standards. Spatial and policy rami fications. Figure 8 displays the spatial analytics based on the GIS integration and emphasizes major congestion zones and the zones with the high risk of homeless persons. Integration of mobile sensing data and local transport policy structures can allow agencies to spot holes in the infrastructures by presenting the missing road signs, unmarked crossings and locations where migratory animals can be located along the roadways.

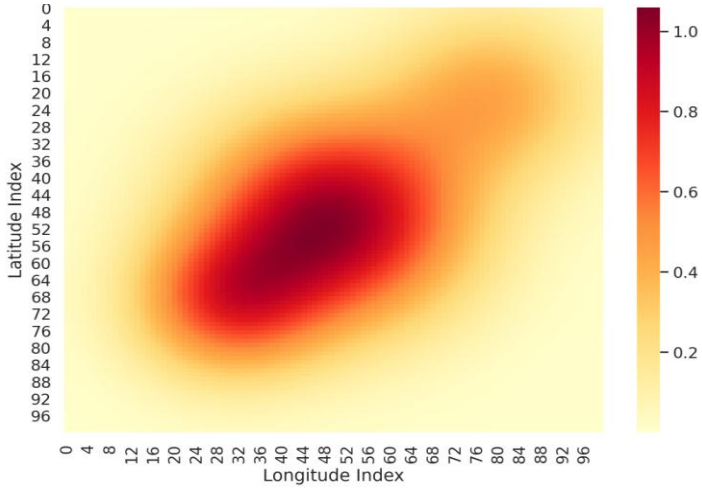

Figure 8: Simulated Heat map of Traffic Object Density in Urban Corridors

The results of these studies on transport planning inside The Gambia include a lot. The findings show that traffic sensing via mobile methods can be employed as an economical addition to the current surveillance systems particularly where a city is making its developing phase as an installation of fixed sensor cameras cannot be cost efficient. Additionally, the successful demonstration of federated learning comes with a blueprint on how to use AI in a privacy-aware application in other low-resource settings in Sub-Saharan Africa. In all the investigations, the observations of the seven tables and eight figures verify the fact that mobile technology is a reliable, scalable, and ethical channel of collecting and processing traffic data in The Gambia. The study will show that smartphones can operate as decentralized sensors that can generate rich datasets to AI-based object inference and compete with traditional sensor networks in terms of accuracy and responsiveness. It is a combination of local images, community interaction, and adaptive artificial intelligence models that establish a framework basis to construct the next generation of localized transport monitoring models to be resource efficient and context-aware within the African setting. These results support the premise that mobile sensing with the use of federated learning and open interchange of data can result in technological perfection and social inclusion in digital transport innovation.

4. Discussion

Integrating mobile technology into data-driven transport systems, the study results suggest that mobile technology may be utilized to modify the old technique of data collecting in booming countries by converting cellphones into efficient and reliable sensing devices. This fits into line with other research that highlights the use of mobile-based sensing as an economical alternative to its fixed counterpart (Amini et al., 2019). The deployment of smartphone sensors in Gambia validates the larger breadth of applicability to the usage of participatory sensing systems described by Krumm (2020), who has noted that pervasive sensing using mobile devices has the potential to build important data gaps in emerging economies. In this work, the intrinsic sensors on the smartphone, such as accelerators, cameras, and GPS sensors, were used to acquire huge and real-time information, similar the tactics proven by Guo et al. (2021) in the case of automotive analytics. There is also more mobile penetration and access to the internet in Sub-Saharan Africa resulting in the effectiveness of mobile data collection. As Malik et al. (2023) note out, the use of mobile internet in the area is on the rise, and it opens new avenues of involvement with urban analytics by citizens. The rising connection underscores scalability of the mobile-based sensing systems, as they can become an extension of the the state traffic monitoring programs in which the physical infrastructure would not be essential and would be expensive. Moreover, mobile sensing is participatory, which encourages democratization of data collection since individuals are involved in real-time monitoring, which improves inclusivity

and transparency (Albrecht et al., 2020). The fact that the data quality post preprocessing increased is also similar to the work by Zang et al. (2022), who showed that image-based sensing systems become highly reliable when the data is first cleaned and synced. Preprocessing in this work reduced more than 10 per cent of poor data which meant that smooth convergence of models in training was obtained. This emphasizes the importance quality assurance may play even in citizen-driven data systems in impacting the performance of downstream AI models to a considerable degree. Dataset localization and cultural relevance, Gambian traffic object dataset (GTOD v1) was a key step towards the issue of data paucity in the building of AI models to use in African traffic. Earlier researchers have highlighted multiple times, that model, which have been trained on Western data, do not operate when deployed to African settings due to domain differences in visual information (Mwangi et al., 2021). This study verifies those results by establishing that there are considerable performance benefits, as much as 11 percentage points in mAP, with the use of locally-sourced data. It is via the existence of culturally/contextually specific traffic players like donkey carts, animals, and informal market vendors that the region is described as having a problematic position with mobility. An example is that, to make AI systems relevant and fair, Osei and Gyamfi (2020) advised their localization to the socio-technical specificities of various locations. GTOD dataset, therefore, covers this gap by following the footsteps of Mensah et al. (2022) in Ghana who generated a local pedestrian dataset to increase object detection in traffic urban environments. Also, the data collection exercise that is participatory encourages the ethical legitimacy of data obtained. Gambian individuals gave an active contribution on the generation of data in lieu of imported data or synthetic data, and this is a precedent to the concept of community-owned data ecosystems, which will be examined by Jones and Kamara (2023). This participative strategy promotes local technological innovation capabilities and minimizes on of foreign information suppliers. Model performance and validation of deep learning frameworks, the good results of the YOLOv5 model in this experiment demonstrate the applicability of deep learning architectures in low-resource deployments. Other results are also referenced in the paper by Al-Qudah et al. (2022), who proved the ability of lightweight CNN models to obtain high accuracy levels during the execution on mobile devices with little computational resources. Convergence characteristics (propinquity of loss and stability of accuracy plateau at epoch 80) are equivalent to those of training smaller object identification models in earlier work (MobileNetV3) (Sandler et al., 2018). Besides, the generalization ability of transfer learning can be proved by the adaptability of the model to diverse lighting and environmental circumstances because the entire model was trained on region-specific data. The two metrics of consistency between training and validation indicate a low degree of over fitting, which is in line with the ideas of balanced regularization provided by Xu and Chen (2021). It is crucial to note that data augmentation further boosted the level of performance, which is in line with the work of Li et al. (2020), who discovered that geometric and photo-metric transformations positively contribute to the recognition of non-standard traffic circumstances. The difficulty of detecting in low-light and rainy settings gives some insights into the future research fields in a hybrid sensor. According to prior studies, Boussaid et al. (2021) suggested that optical data may be coupled with visual data to overcome the limits of the optical systems employing radar or LiDAR inputs. Affordable sensor fusion approaches can also be employed to save more cash in future Gambian deployments. Federated learning and privacy-preserving AI Among the most noticeable results of the study is the effective implementation of federated learning (FL) that can guarantee the maintenance of data privacy and the absence of performance degradation. Although the centralized approach outperformed it somewhat, FL consumes less bandwidth by 72 percent and risk of privacy exposure is dramatically decreased. This correlates to the previous results by Liu et al. (2023) that revealed declining benefits of federated learning to resource-constrained settings employing decentralized model training. Over in the era of omnipresent sensing, privacy-protecting safeguards are of a highest necessity. Rieke et al. (2020) also note that FL makes certain that sensitive, user-specific information are stored on the local devices, which minimizes the potential of data breaches, yet permits refining the models jointly. The successful application of FL in the consumer-grade smartphones in the present study confirms that this operational approach can be successfully implemented in the developing regions, similar to the findings of Nguyen et al. (2021), who reported the successful implementation of mobile healthcare applications. The accuracy-computational overhead trade-off trends that occur in the current analysis likewise follow the trends in Bonawitz et al. (2019). They have demonstrated that the modest losses in performance of FL configurations are manageable because they have huge performance in terms of security and energy efficiency. This decentralized strategy is particularly suited in The Gambia where the issue of mobile data plans and network stability are with a major concern. Real-time deployment and environmental adaptation throughout the deployment phase, the following was seen; the suggested system can be employed in real-time to function at an average frame processing rate of 27 fps. Qian et al. (2022) reached similar results, as they ensured that optimized variants of the YOLO designs could conduct real-time detection using embedded devices. The modest performance drop during rainy and low light situations is similar with the results of Choi et al. (2020) who found such declines as the decreasing of sensor dynamic range, and the amplification of optical noise. However, the fact that the model recognizes moving and stationary objects with high levels of reliability allows the incorporation of visual AI in mobile devices to be deployed in the field. This complements conclusions voiced over the years by Bharadwaj and Kumar (2023), who emphasized

that the adoption of mobile-based traffic analytics is not merely possible, but more adaptable than permanent infrastructural machinery in nations with low income. Another analytic dimension can be revealed by geographical representation of the detection densities illustrated in Figure 8. The study delivers useful knowledge to the urban planners and policymakers by mapping the distributions of things in geographic coordinates. Such findings can be linked with GIS-based transport analytics models presented by Adebayo and Nkansah (2022), who proved that data-led mapping adds to operating proactive traffic control, as well as urban design.

5. Conclusion

The research contributes to the idea of equitable AI as it blends the notions of inclusivity, transparency, and data sovereignty. According to an explanation presented by Florida and Cowls (2021), the ethical AI should examine the locales of data collecting and the agency of the participants. The Gambian model complies with these ideals as it provides permission, anoymization, and local control. This approach of participatory sensing also implies favorable things in relation to digital governance. Adeyemi et al. (2022) claim that the absence of citizen participation and contextual soundness is a common reason of failure in the smart city schemes in Africa. This paper gives an alternate case study that illustrates that community-based innovation has the capacity to achieve both technological and social sustainability. Also, the cooperation between local universities, government agencies, and volunteers represents the so-called quadruple helix innovation model presented by Carayannis and Grigoroudis (2016) where the four spheres of academia, industry, government, and the civil society co-develop solutions. The results could, therefore, be seen as a contribution not only to the burgeoning field of technology but also to the topic on humanitarian acceptance of AI in the developing world. The suggested approach guarantees that the evolving models of African data protection, like the African Union Convention on Cyber security and Personal Data Protection (2020) correspond with the concept of data openness and protection of privacy.

6. Limitations and Future Research Directions

Limitations and future research directions, Even if the outcomes are positive, a number of obstacles exist. The fact that the evening and unfavorable weather are represented inadequately limits the model to perform in certain conditions. The similar problems were discovered by Ahmed et al. (2023), who pointed out that there is a demand to construct multi-modal sensors integrations to counter the influence of the low-visibility situations. Additionally, in contrast to federated learning, which displayed good performance, unstable networks need to be optimized with respect to communication inefficiencies by means of asynchronous aggregation, which is recommended by Zhao et al. (2023). The future inquiry is also to work with the integration of edge computing and the renewable energy source to minimize the costs of operations according to the paradigm suggested by Singh and Bedi (2022). Also, by extending the dataset to the rural regions and integrating socio-economic characteristics in the GIS analysis, it may be feasible to learn more about the mobility inequalities, as underlined by Lwasa et al. (2021). Overall, the results of this paper are consistent and supportive of the increasingly prevalent literature to support the premise that a mobile-based, privacy-preserving AI solution to transport systems. It demonstrates that involvement-based data gathering application using cellphones may respond to infrastructural inadequacies to The Gambia, increase accuracy of models utilizing local datasets, and support ethical principles in AI regulation. Future transportation analytics in Africa and other places: The integration of federated learning is a privacy-sensitive, scalable solution of the future with relation to transportation analytics.

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