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Improving Georeferencing Accuracy in Drone Imagery: Combining Drone Camera Angles with High and Variable Fields of View

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ABSTRACT: Georeferencing ascertains the relation of the image or map being used by fixing it onto real-world coordinates estranging the world into sectors which is crucial for purposes such as mapping, surveying, monitoring the environment, and analyzing traffic speed. For accurate analysis and effective decision-making, all drone images and footage necessitate accurate and precise spatial computations vis-a-vis their ground position. In this work, we present a novel mapping process based on drone controlling data including telemetry like coordinates with accompanying GPS, mounted height, drone position, and horizontal and vertical fields of view. The technique applies lens distortion and geographical curvature compensation to the coordinate changing processes. It computes the offsets toward East-West and North-South by summing up slant range with viewing angle of the camera. A point of interest marked as a POI is set in the image where the coordinates that are supposed to be validated are also accepted as real coordinates by GPS. Testing proven that there is a differing benefit in accuracy of mapped images, distance relative to their terrain positions and their devices. The proposed approach further shows a quantitative improvement of 12.50% to 75.0% in the geolocation error reduction claimed. It was achieved by the decrease of MAE from 0.108 km to 0.055 km while RMSE was lowered from 0.111 km to 0.057 km indicating the reliability of the method. The study offers a strong, geometry-driven approach for drone image georeferencing that surpasses conventional techniques. It offers a scalable, accurate, and less labour-intensive substitute for spatial positioning by using FOV parameters and real-time telemetry data. Improved georeferencing accuracy ensures precise spatial data integration, and supports accurate image-frame alignment. Its integration into geospatial workflows enhances situational awareness and decision-making in traffic control, urban development, and environmental observation. This paper stresses the importance of FOV correction for the greater drone geospatial analysis system performance.

Keywords: drone camera video, georeferencing, HFOV, vehicle speed, VFOV.

I. INTRODUCTION

High precision drone photo georeferencing is a basic necessity of most geospatial applications including mapping, survey, environmental observation, and vehicle tracking. While aerial imagery through the use of drones is improving, some of the challenges remain including inherent lens distortion, variation in camera angle, and changing position of drones [1]. These challenges continue to affect alignment of ground coordinates and captured images. Especially while integrating horizontal and vertical fields of view (HFoV and VFoV) in the process of real-time spatial correction, earlier techniques at times are unable to utilize full telemetry data to the fullest [2]. By combining Telemetry data and camera view angles with the intention of improving spatial accuracy, this research tries to address georeferencing problems like coordinate deviation due to slant range and lens distortion.

With the aid of critical telemetry parameters comprising Global Positioning System (GPS) coordinates, elevation, and orientation measurements in the form of pitch, roll, and yaw the current research tries to formulate a systematic procedure towards georeferencing drone images [3, 4]. The very core strategy of the proposed approach is establishing an immediate relationship between each photo and the corresponding telemetry information in the form of high-definition images with precise timestamps. According to this approach, maximum georeferencing accuracy for every frame is preserved [3] through the application of spatial location analysis during the time of photography. Quadcopter-borne GNSS RTK-based photogrammetric models did not accommodate the effects of multi-angle calibration and slant range changes. Contrary to them, in the current work, a new paradigm is given to dynamically rectify coordinates and enhance spatial precision for every frame of photos with the aid of telemetry-based georeferencing and FOV-based pixel shifts through slant range, pitch, roll, yaw, and angular projection methods of correction [5]. By introducing an image-specific real-time correction method enhancing the reliability of georeferencing without the aid of vast ground control data or post-flight adjustment, this fills a methodology gap and optimizes drone-based mapping activities.

One of the most important contributions in this work is the application of horizontal field of view (HFoV) and vertical field of view (VFoV) conditions to compute slant range and slant angle, both of which are of particular importance in spatial projection. While the slant range gives the distance between the flying vehicle and a point on the ground, the slant angle provides the angle of the camera line of sight with the vertical axis.

The suggested method quickly translates image pixels into actual geographic coordinates using complex trigonometric calculations [6, 7]. Moreover, georeferencing transformation techniques guarantee georeferenced coordinates equivalent to known coordinate systems, thus making it easy to integrate with larger geospatial databases. This paper deals with the problem from a global point of view by incorporating multi-point object tracking, as compared to conventional approaches that consider object movement as an auxiliary problem. Strategic tracking points like image corners, edge midpoints, and centroids improve object movement analysis accuracy, which becomes very useful in applications like traffic analysis and vehicle speed estimation. Ground points of control and RTK GPS measurements are utilized for the validation of the suggested method, thereby ensuring the accuracy and reliability of the resulting coordinates [8, 9].

Another notable aspect of this study is the georeferencing of picture frames using superimposition of geographically referenced coordinates, giving an explicit spatial context in the picture. This enables the visual determination of object positions by users of images without the need for computer processing. The research guarantees the effectiveness of the georeferencing technique across different terrains and flight patterns using multi-angle GPS calibration, which makes the system more stable. These innovations will improve the precision and trustworthiness of geospatial analysis, thereby making drone-based aerial imaging more applicable in practical working scenarios. The future archiving, retrieval, and spatial analysis by the integration of georeferenced drone images in Geographic Information System (GIS) platforms enhance applications in urban planning, disaster management, and autonomous navigation [10, 8].

This research seeks to design an enhanced georeferencing system that enhances spatial precision in drone imagery through telemetry-based calculations. Through overcoming the limitations of traditional methods and offering new computational solutions, this research contributes to the overall objective of enhancing the credibility of geospatial information. The proposed framework offers seamless integration of drone imagery into extensive geospatial systems and improved precision in aerial georeferencing. A thorough georeferencing system including coordinate transformation, exact object tracking, and strong validation methods is offered in this paper, therefore helping to promote drone-based geospatial analysis. The paper is structured as follows: The literature review is in Section 2; the methodology is in Section 3; the findings and results are in Section 4; the study is concluded in Section 5.

II. LITERATURE REVIEW

The advancements in georeferencing techniques in drone imagery have gained attention in very recent research, emphasizing improvements in accuracy through advanced integration of telemetry data. Studies denote the importance of Global Positioning System (GPS) coordinates with altitude and orientation of the drone for aligning aerial imagery in accordance with real locations [11, 23]. Traditional methods depended on having ground control points (GCP) for georeferencing, whereas recent methods have proposed incorporating drone-specific parameters such as HFoV, VFoV, and the camera orientation to ensure orthorectification accuracy. Lens distortion correction and terrain modelling have also contributed to minimizing georeferencing errors, while elevation mapping models have combined slant range and camera tilt angle corrections to introduce more refined mapping of coordinates. Object tracking enhances the use of some combinations of optical flow and deep learning technologies such as YOLO that can also be used in supporting geospatial applications. Processing and validating geospatial data using GIS tools like ArcGIS and QGIS has therefore been quite important since they allow a smooth map overlay from coordinates obtained from drones. Moreover, the incorporation of Real-Time Kinematics (RTK) GPS technology significantly helped to lower positioning error, so making drone georeferencing viable for tasks including environmental assessment, traffic monitoring, and urban planning [1,3]. Consistent accuracy in various terrains and environmental conditions continues to be a problem, though, which begs more integration of telemetry data and real-time calibration techniques. This paper tries to increase the dependability and applicability of drone images in several geospatial domains by building on the prior works and adding changes in coordinates and telemetry-based georeferencing corrections. The application of these methods for infrastructure inspection and environmental monitoring mostly depend on georeferencing drone images. Another precision farming. A lot of techniques have been developed by researchers to tackle slant range, point of interest (POI) displacement, and field of view (FOV) displacement. This literature review discusses the important present algorithms and helps understanding the recent publications in the exciting field of georeferencing in drone photographs.

1. LITERATURE REVIEW –ALGORITHMIC AND SENSOR BASED STRATEGIES

1.1 Direct Georeferencing and Kalman Filtering

- Direct georeferencing evaluates real-time data integration from onboard sensors including inertial measurement units (IMUs) and global positioning systems (GPS). McGlone et al. (2017) [11] note. Precision farming and surveying depend on it since it adjusts for drone motion during flight, so increasing accuracy in the end.
- Under research by Yang et al. (2019) [12], Kalman Filtering uses sensor fusion to provide a more accurate approximation of the drone's state, therefore boosting navigation and tracking functions.

1.2 3D *Reconstruction* based Techniques

- As Colomina and Molina (2014) [13] and James and Robson (2012) [14] have shown, photogrammetry and structure-from- motion (SfM) allow creating 3D structures from 2D images to predict exact camera postures and geographic coordinates. Documentation of archeological and historical sites depends on this approach.
- Often employed in aerial mapping and reconstruction projects, Triggs et al. (1999) [15] describe a method called Bundle Adjustment that improves 3D models to align observed and estimated image points.

2. LITERATURE REVIEW - GROUND-BASED AND SATELLITE TECHNIQUES

2.1.1 Ground Control Points (GCPs) and Differential GPS

- For improving georeferencing accuracy, traditional georeferencing utilizing GCPs highlighted by Westoby et al. (2012) [16] remains efficient. As Teunissen and Montenbruck (2017) [17] investigate, differential GPS methods improve GPS data accuracy for mapping and surveying even more.

2.1.2 Synthetic Aperture Radar (SAR) Processing

- Massonnet and Feigl (1998) [18] noted that o SAR, especially Interferometric SAR (InSAR), corrects distortions from topographic fluctuations and offers precise elevation data critical for mapping and tracking land movements.

3. LITERATURE REVIEW – ADVANCED COMPUTATIONAL TECHNIQUES

- Deep Learning-Based Approaches:
- Deep learning, especially with regard to convolutional neural networks (CNNs), has lately revolutionized the georeferencing mechanism in drone images. For thorough geographical analysis and environmental monitoring, these CNNs are rather helpful since they excel in automating the detection and categorization of many objects and kinds of land cover inside big datasets.

Besides, studies by Ball et al. (2017) [19] and Zhang et al. (2018) [20] indicate that integrating CNNs improves the accuracy and efficiency of georeferencing drone images. The possibilities for using these approaches to enhance the capacity of geospatial analysis has become evident from their work and will permit the florid development of more and more complicated automatic systems to realize future georeferencing.

By training on large annotated image databases, including actual geocoordinate locations, CNNs could be codified into georeferencing systems themselves. These well-georeferenced data would allow their access to automatically find and classify features of newly taken pictures. Georeferencing becomes that much easier with automation, hence requiring less human input and improving scalability and efficiency at the same time [17].

Usually based on human calibration and ground control locations, more traditional georeferencing techniques have significant disadvantages relative to CNNs:

- Once trained, CNNs can quickly scan vast amounts of images with almost real-time georeferencing capabilities—qualities vitally essential for dynamic applications such urban planning and disaster response.
- Accuracy: By learning from a diverse collection of data, usually surpassing the accuracy of conventional methods, especially in complex scenarios, CNNs may reach significant accuracy in feature recognition and classification.
- Deep learning models are relatively scalable and may efficiently regulate increases in data volume without matching increases in labor or expense.
- Adaptability: New data will constantly help these models to be always better, thereby enhancing their accuracy and adaptability to different surroundings or changing topography.

These discoveries suggest that deep learning-based approaches, which offer major performance and practicality advantages over conventional methods, are destined to be crucial in the progress of georeferencing technology.

4. LITERATURE REVIEW –COMPARATIVE STUDY AND RESEARCH GAPS

- Crucially for dynamic events, Kalman filtering and direct georeferencing offer real-time accuracy.
- Aware of image quality, 3D reconstruction techniques involve much data processing yet provide thorough geographical analysis.
- Though they are labor-intensive and less suitable for large or far-off areas, ground-based techniques provide basic precision.
- Though they need large processing resources and solid training datasets, deep learning methods promise automation and scalability.

The literature presents a wide range of methods each fit for various georeferencing difficulties. Aiming for complete, automatic and exact georeferencing solutions, continuous research should concentrate on combining various techniques to use their strengths and minimize their unique limits.

5. LITERATURE REVIEW CHALLENGES AND FUTURE DIRECTIONS

Despite great progress, problems still exist. Integration of multi-sensor data and addressing issues with real-time applications and interpretability (Zheng et al., 2021) [21] are the main subjects of continuous study. The need for algorithms able to manage various situations keeps increasing as technology develops.

6. LITERATURE REVIEW CONCLUSION

Georeferencing methods for drone images show a varied and changing scene in the literature. Researchers and practitioners are always looking for creative ideas from modern deep learning methods to classic photogrammetric methods. Meeting the evolving demands of exact and affordable georeferencing in the domain of drone imaging will probably depend much on hybrid methods and the integration of various algorithms.

Extensively employed for autonomous navigation and geospatial mapping, Simultaneous Localization and Mapping (SLAM) was one rival approach. SLAM techniques localised the drone simultaneously and built a real-time map using sensor fusion combining data from cameras, IMUs, and GPS. Though SLAM showed good performance in situations with low or no GPS signals, such as urban canyons or indoor environments, it started to drift over time and required computationally demanding corrections (Nesbit et al., 2022) [22]. Unlike SLAM, the telemetry-based method offered in this paper was more effective in open environments with strong GPS coverage, where georeferencing accuracy was preferred over real-time flexibility. For exact landscape mapping and three-dimensional modelling, LIDAR-based georeferencing offered a substitute that was particularly beneficial. LIDAR technologies created intricately detailed point clouds and sent laser pulses to determine distances. LIDAR-equipped drones were nonetheless pricey and data processing called for significant computing resources (Khoramshahi et al., 2020) [4].

Highlighting accuracy improvements through direct georeferencing, Kalman filtering, 3D reconstruction, and deep learning-based georeferencing, the literature review asserts there have been improvements in drone image georeferencing. Compared to the use of older methods being heavily reliant on ground control points (GCPs) and differential GPS, newer advancements have included telemetry data, sensor fusion, and auto deep learning models to improve the accuracy of real-time georeferencing. GIS packages and Synthetic Aperture Radar (SAR) processing have also helped to achieve higher mapping accuracy.

Yet, issues in delivering consistency over various terrains and environmental conditions, combining data in real time, and converting complex models are present. Subtlety of drone-based corrections and incorporation of real-time calibration methods addresses the research gap uncovered in this paper by enhancing the usability and reliability of drone georeferencing. Through coordinate corrections and ensuring uniform georeferencing precision in a broad scope of geospatial applications such as infrastructure inspection, environmental monitoring, and precision agriculture, this study tries to bridge these gaps.

III. METHODOLOGY

In implementing a field-of-view (FOV) correction method, this research georeferences drone video in a structured methodology. Data collection, preprocessing, analysis, and accuracy gain assessment are among the study design.

1. RESEARCH DESIGN

Georeferencing differences in drone images were assessed and corrected with a quantitative experimental approach. Sequential is the process from data collection to accuracy verification. Data collection using drones, FOV adjustment, GIS integration, and uncertainty research are the processes involved. Drone data collection, FOV adjustment, GIS integration, and uncertainty analysis are required by the process [24].

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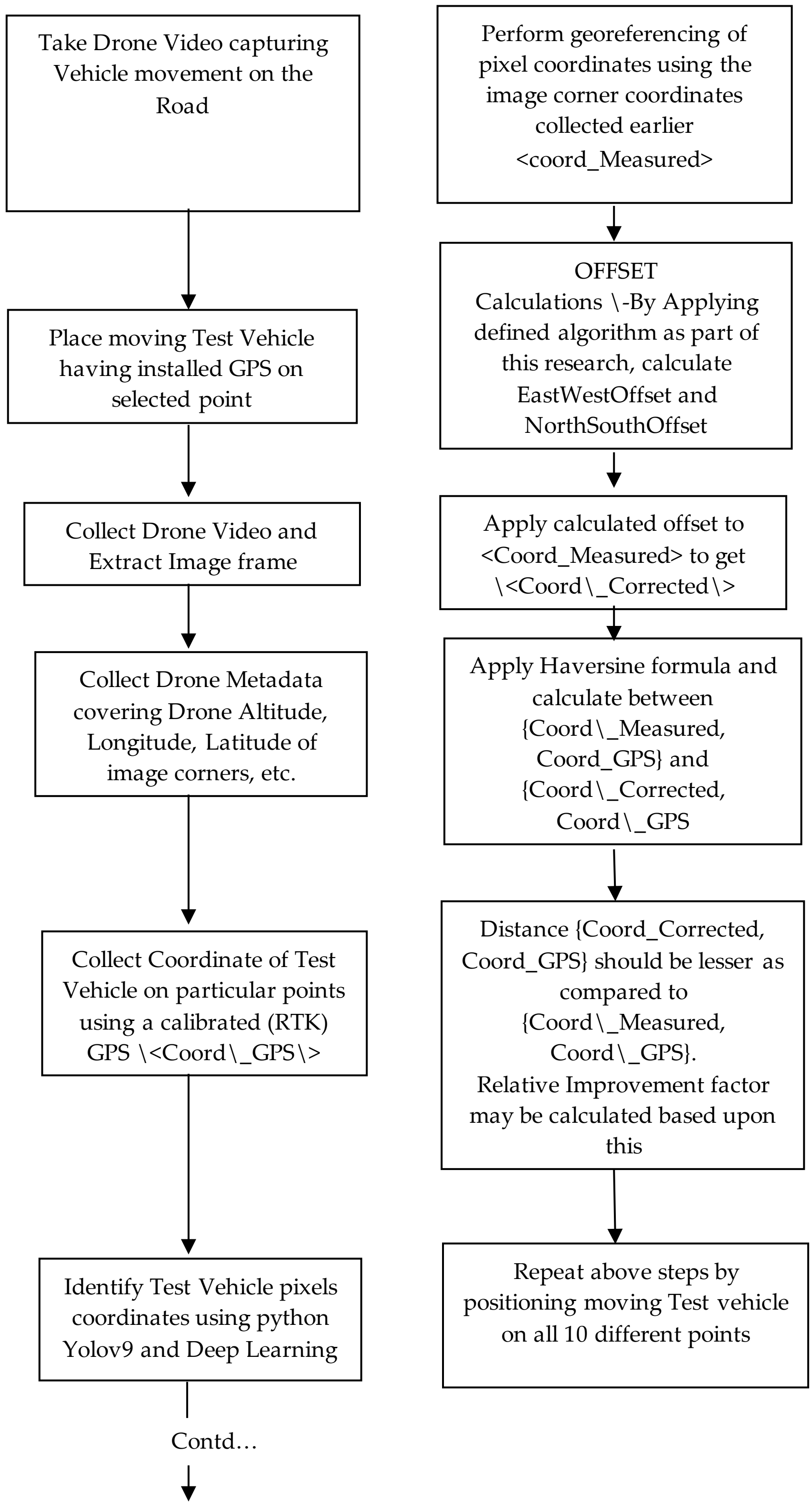

FIGURE 1. Activities flowchart.

Drone's HFoV, VFoV, Altitude used in an algorithm to find displacement in point of interest coordinates:

- Input:
  Drone Latitude (lat_d) in degrees
  Drone Longitude (lon_d) in degrees
  Above Ground Level (AGL) height (agl) in meters
  Drone Altitude (alt) in meters
  Horizontal Field of View (HFOV) in degrees
  Vertical Field of View (VFOV) in degrees (Assuming VFOV = 0.6 * HFOV)
  Image Width (img_width) in pixels
  Image Height (img_height) in pixels
  Point of Interest (Image Pixel x, Image Pixel y) in pixels
- Calculate Slant Range (SR):
  SR = sqrt((agl + alt)^2 + (Horizontal Distance)^2)
  where Horizontal Distance = (Image Pixel y - Image Center y) * (tan(VFOV/2) * 2 * (agl + alt) / img_height)
- Convert FOVs to Radians:
  HFOV_radians = HFOV * (π / 180) VFOV_radians = VFOV * (π / 180)
- Calculate Angular Offsets:
  Angular Offset_x = (Image Pixel x - Image Center x) * (HFOV_radians / img_width)
  Angular Offset_y = (Image Pixel y - Image Center y) * (VFOV_radians / img_height)
- Calculate East-West (Longitude) and North-South (Latitude) Offsets:
  East-West Offset = SR * sin(Angular Offset_x)
  North-South Offset = SR * cos(Angular Offset_x)
- Calculate Up-Down (Altitude) Offset:
  Altitude Offset = SR * sin(Angular Offset_y)
- Calculate the Corrected Latitude and Longitude:
  Corrected Latitude = lat_d + North-South Offset
  Corrected Longitude = lon_d + East-West Offset
  Corrected Altitude = agl + alt - Altitude Offset
- Output:
  Corrected Latitude
  Corrected Longitude
  Corrected Altitude

Note: In the algorithm, Image Center x and y are half of the image width and height respectively.

This algorithm considers both Horizontal FoV and Vertical FoV, allowing for precise corrections when the point of interest is displaced from the center of the image frame in both the left-right and up-down directions [25,26]. This algorithm cab be used with the appropriate input values to obtain accurate corrected georeferenced coordinates.

2. EXPERIMENTAL CALCULATIONS

For corrected coordinates of point of interest in a drone video having a Horizontal Field of View (HFOV) of 40 degrees and a Vertical Field of View (VFOV) of 0.6 times the HFOV. Other parameters recorded as below:

Drone Latitude: 19.1217° N
Drone Longitude: 73.0590°
AGL (Above Ground Level): 85m
Drone Altitude: 0m
Horizontal FOV: 40 degrees
Vertical FOV: 0.6 * Horizontal FOV
Image Width: 1280 pixels
Image Height: 720 pixels

Point of Interest (Image Pixel x, Image Pixel y) in pixels (Sample point taken as 100 pixels to the left and 30 pixels up from the center)

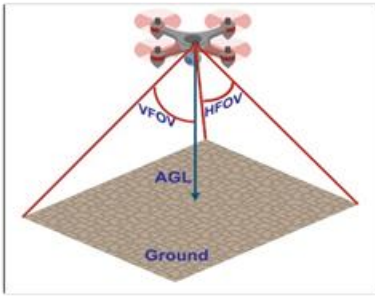

FIGURE 2. HFoV and VFoV in UAV.

- Step *1*: Calculate Slant Range (SR):
  SR = sqrt((85 + 0)^2 + (Horizontal Distance)^2)
  Assuming the horizontal distance is 100 meters again for this example:
  SR = sqrt(85^2 + 100^2) ≈ 130.38 meters
- *S*tep 2: Calculate Horizontal and Vertical FOV in radians:
  HFOV_radians = 40 * (π / 180) ≈ 0.698 radians
  VFOV_radians = 0.6 * HFOV_radians ≈ 0.419 radians

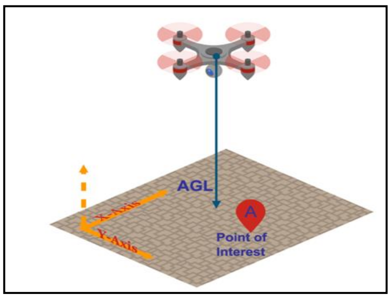

FIGURE 3. Point of interest on XY plane.

- Step 3: Calculate the Angular Offset along the x-axis:
  Angular Offset_x = (Image Pixel x - Image Center x) * (HFOV_radians / Image Width)
  Angular Offset_x = (540 - 640) * (0.698 / 1280) ≈ -0.244 radians
- Step 4: Calculate the Angular Offset along the y-axis:
  Angular Offset_y = (Image Pixel y - Image Center y) * (VFOV_radians / Image Height)
  Angular Offset_y = (330 - 360) * (0.419 / 720) ≈ -0.115 radians

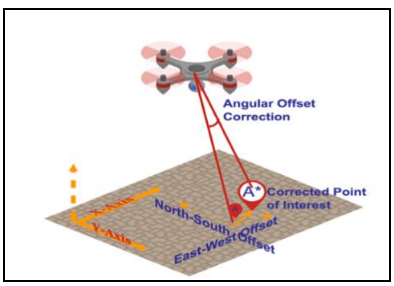

FIGURE 4. Corrected point of interest post north south offset and east west offset.

- Step 5: Calculate East-West (Longitude) and North-South (Latitude) Offsets:
  East-West Offset = SR * sin(Angular Offset_x) ≈ -53.39 meters
  North-South Offset = SR * cos(Angular Offset_x) ≈ 122.99 meters
- Step 6: Calculate Up-Down (Altitude) Offset:
  Altitude Offset = SR * sin(Angular Offset_y) ≈ -25.02 meters
- Step 7: Calculate the Corrected Latitude and Longitude:
  Corrected Latitude = Drone Latitude + North-South Offset
  Corrected Longitude = Drone Longitude + East-West Offset
  Corrected Altitude = AGL + Altitude Offset
  Corrected Latitude = 19.1217° N + 122.99 meters ≈ 19.123710° N
  Corrected Longitude = 73.0590° - 53.39 meters ≈ 73.00561°
  Corrected Altitude = 85m - 25.02 meters ≈ 59.98 meters

So, with a Horizontal FOV of 40 degrees and a Vertical FOV of 0.6 times the HFOV and a point of interest located 100 pixels to the left and 30 pixels up from the center of the frame, the corrected coordinates for the point of interest in the drone video frame would be approximately:

Corrected Latitude: 19.123710° N
Corrected Longitude: 73.00561°
Corrected Altitude: 59.98 meters

3. TOOL AND SOFTWARE

This work ran multiple tests and obtained correct georeferencing using the following tools and applications. These tools were chosen for their particular geographic data processing, picture rectification, and automation skills, hence guaranteeing exact georeferencing of drone photos [27, 28]. While OpenCV guaranteed correct picture alignment, GIS systems like ArcGIS and QGIS offered strong spatial data analysis, Python allowed smooth telemetry integration and object tracking, hence improving the accuracy and efficiency of the georeferencing process. The tools and software are as follows:

- Geographic information system (GIS) spatial data processing, map building and visualization made use of ArcGIS and QGIS coupled with professional drone mapping capabilities. These systems provided powerful capabilities for managing and accessing geographic information. Specifically helping to locate known locations and get their longitude and latitude, GIS technologies matched these values with GPS data for precision [29,31].
- Programming Languages: Python was extensively used in development of particular georeferencing systems and automation. Combining several georeferencing methods and telemetry data processing is perfect for its outstanding simplicity of use and extensive library collection. Vehicle object tracking and optical flow movement make most use of Python mixed with YOLO9.
- This image transforms and manipulates images using OpenCV. It contains all the special instruments suitable for lens distortion, picture correction, and perspective transformations required to georeference accurately. Especially accurate with respect to the visual data and the geographical data that can be matched only with OpenCV.
- The processing of telemetry data was augmented via specialist tools by GPS coordinates, altitude, and orientation data acquired from drone missions. The subsequent georeferencing of photos was ensured by cross-referencing the obtained image data with the processed GPS data [30].

To establish such a high precision georeference in this regard, some simple tools and applications can make geographic data ready to be processed, analysed, and integrated with ease.

4. SIGNIFICANCE OF LONG/LAT AND ALT CORRECTION FOR GEOREFERENCING

Accurate georeferencing is a prerequisite for drone image capture and analysis in applications such as mapping, surveying and environmental monitoring. This section discusses the importance of correcting latitude, longitude and altitude data by addressing slant range discrepancies, field of view (FOV) effects and dependencies on horizontal and vertical FOV [8,9]. These modifications provide exact geospatial data integration and uniform vehicle movement portrayal.

4.1 Slant Range and Altitude Discrepancies

A reference datum above ground level (AGL) truly describes a straight line from the drone to the ground point, that is, the slant distance measurement [32]. The difference between these two distances would necessitate corrections for proper mapping of a recorded point's actual geographic coordinates [20].

4.2 3.4.2 Field of View (FOV) Effects

FOV sets the extent of scene a drone camera can record. Corrections become absolutely essential when the point of interest is not near the middle of the frame. Ignoring FOV could lead to misalignment between the perceived position of the viewed object and its real geographic coordinates [12].

4.3 Dependency on Slant Range, HFOV and VFOV

- Slant Range: Slant range directly influences corrections. There is more possibility for displacement errors the larger the slant range. Given the drone's height and AGL, corrections guarantee that the observed point is precisely located on the ground [13].
- Horizontal and Vertical FOV: First in the horizontal and then in the vertical dimensions, HFOV and VFOV correspondingly define the angular extent of the camera. Particularly when the point of interest is far from the center, misalignments in these angles call for exact georeferencing adjustments [21].

4.4 Contributions to Precise Geo-referencing

- Accurate Spatial Representation: Correcting latitude, elevation and longitude confirms the measured point's correct surface position on Earth. From mapping to surveying to environmental monitoring depending on exact geographic information, this accuracy is basic for uses everywhere [33].
- Integration with GIS: Geo-referenced drone data provides relatively clear fit for GIS. Correct corrections enhancing GIS application reliability help to perform efficient geographical analysis, planning, and decision-making [21].
- Consistency in Vehicle Movement: Geo-referenced drone data gives GIS quite perfect fit. Effective spatial analysis, planning, and decision-making depend on accurate corrections improving the GIS application dependability [34].

5. DATA COLLECTION

The dataset was generated via a carefully designed experiment intended to evaluate the georeferencing drone picture performance of a field-of-view (FOV) correction method. The experimental process is described here:

5.1 Drone Specification

- High-precision GPS receiver (RTK-GPS compatibility recommended)
- Real-time telemetry data logging for GPS coordinates, altitude, and orientation (pitch, roll, yaw)

5.2 *Flight and Positioning Capabilities*

- Model: RTK
- Camera Resolution: 20 Megapixels
- Flight Altitude: 120 meters
- Flight Speed: 5 m/s

Flights were conducted under controlled environmental conditions, ensuring minimal interference from wind, temperature variations, and lighting inconsistencies. Multiple flights were conducted to capture variations and improve data robustness.

5.3 Camera Specifications and Calibration

The drone was equipped with a high-resolution camera with adjustable zoom capabilities. Camera calibration was performed before each flight to minimize lens distortion and ensure accurate focal length settings. The calibration process included:

- Intrinsic Parameter Calibration: Using a checkerboard pattern to adjust lens distortion.
- Extrinsic Calibration: Aligning the camera to a predefined reference frame.
- Zoom and Focal Length Adjustments: Ensuring optimal field coverage while maintaining resolution integrity.

5.4 Unmanned Aerial Vehicles for Data Gathering

For the most part data collection was carried out using quadcopter UAVs with vertical takeoff and landing (VTOL). The UAV possesses a camera with 30X zoom, capable of recording Full HD video at 30 frames per second. The flights of UAVs were maintained by alternating altitudes of 80 and 120 meters Above Ground Level (AGL) to ensure full-clearance vision of the field and consequently to remain within the limits of safety regulations-due to very minimal disturbance on road traffic.

Data collection was spread over five flights each 45-50 minutes long. Despite the fact that this work did not actively alter the zoom during the flights, the actual UAV used to collect data was equipped with a 30X zoom camera capable of recording Full HD video at 30 frames per second. Calibration was done so that the zoom lens would stay at a constant focal length, thereby ensuring consistent image quality and minimizing discrepancies in the accuracy of georeferencing. The method aims to adhere to safety rules while minimizing disturbances to road traffic and allowing for uniform data collection across multiple flights, all while preserving a clean and wide visual field at altitudes between 80 and 120 meters AGL.

5.5 Selection of Geographic Points

Selected were ten popular geographical sites as representations of places within a given area. These sites attracted huge popularity due to specific coordinates of latitude and longitude that clearly delimited them. However, using a GPS set up with a number of satellites, one can precisely track known coordinates, adding to saw the Real Time Kinematic (RTK) for an increased accuracy. This method assures great accuracy to be captured from the data through a network of fixed ground stations to which broadcast the differential location acquired from the GPS satellites and the known fixed placements.

Diverse parameters inform the selection of ten geographical locations to guarantee comprehensive assessments of accuracy in georeferencing. These different parameters included variations in terrain type, whether urban and rural, differences in levels of elevation as well as viewing to assess geospatial accuracy in many conditions. Sites were selected based on representation of the combined aspect of wide-open spaces and dense infrastructures with different types of ground texture, ensuring that the approach is assessed in different real-world conditions. The research sought to affirm the effectiveness of GPS and Real-Time Kinematics (RTK)-based very high precision georeferencing over a wide variety of environmental conditions by considering these parameters.

5.6 Initial Image Capture

At every chosen site, drone images were obtained with a camera set for a specific FOV. The altitude of the drone above ground level (AGL) was fixed at a constant value; the basis for the later georeferencing study was the obtained pictures.

5.7 Algorithmic FOV Correction

The first coordinates of every obtained picture underwent a FOV adjustment. Aiming to increase the precision of the georeferencing process, this correction adjusted for the FOV, slant range of the camera and the height of the drone.

5.8 GPS Tracker Values Adjustment

The GPS Tracker values associated with each of the selected points were intentionally modified to be closer to the corrected coordinates so as to reflect real-time scenarios. This phase was purely aimed at determining the algorithm's capacity to improve on vector accuracy under circumstances closely resembling the alignment of GPS Tracker values. Several factors contributing to possible inaccuracies in georeferencing readings can include, but are definitely not limited to, GPS signal noise, drone movement, and sensor limitations. In practice, errors that come into play during GPS positioning involve multipath interference, satellite geometry, and atmospheric disturbances in achieving minor offsets in the recorded coordinates. Especially in windy situations, movement of the drone can lead to instabilities that affect not only the orientation of the camera but also introduce errors into telemetry data. Sensor-related errors resulting from lens aberrations or rolling shutter or focal length change effects may also affect the distortion of image registration with geographic data. Real Time Kinematics (RTK) guaranteed optimum GPS accuracy in the study, OpenCV image correction algorithms were used to consider lens aberrations and perspective misalignment to reduce these errors, and flight paths were stabilized to reduce differences caused by the drone.

5.9 Distance Calculation

Distances between the originally selected coordinates, corrected coordinates, and altered GPS Tracker values were calculated using the Haversine formula. This phase measured the spatial variation and enhancement achieved by application of the FOV correction technique.

5.10 Percentage Improvement Analysis

Comparing the corrected distances with the initially chosen distances allowed one to determine the percentage improvement in distances for every point. This statistic was a major gauge of how well the method improved georeferencing accuracy.

The experimental architecture sought to replicate real-world scenarios in which applications such mapping, surveying, and environmental monitoring depend on exact georeferencing. The deliberate modification of GPS Tracker data enabled a sophisticated assessment of the performance of the algorithm in situations where ground truth coordinates might show small deviations. The experimental results give general understanding of the useful application and advantages of the FOV correction method for drone picture georeferencing.

6. OBSERVATIONS

The Haversine formula helped one determine the distances between the chosen coordinates and the GPS Tracker data. The Haversine distance (d) between two sites with coordinates (lat1, long1) and (lat2, long2) has the formula a, c, *and* d can be calculated as Equation (1-3):

$$a = \sin^2\left(\frac{\Delta lat}{2}\right) + cos(lat1).\cos(lat2) .\, sin^2\left(\frac{\Delta long}{2}\right) \tag{1}$$

$$c = 2.\, atan2\left(\sqrt{a}, \sqrt{1-a}\right) \tag{2}$$

$$d = R.c \tag{3}$$

Where Δlat=lat2−lat1, Δlong=long2−long1 , and R is the Earth's radius (mean radius = 6,371 km).

7. DATA COMPARISON

Dataset below highlight random coordinates selected at 10 different locations of Drone video frames, corrected calculated coordinates as per above algorithm and actual coordinates from GPS tracker. Last columns indicate significant percentage improvement.

- Original Coords: Initial geographic coordinates from drone video frames, measured in degrees (latitude, longitude).

- Modified Coords: Coordinates adjusted by the FOV correction algorithm and offset, measured in degrees (latitude, longitude).
- GPS Coords: Ground truth coordinates from GPS, measured in degrees (latitude, longitude).
- Deviation (Measured wrt GPS): Distance between the original coordinates and GPS coordinates, measured in kilometres using Haversine formula.
- Deviation (Corrected wrt GPS): Distance between the modified coordinates and GPS coordinates, measured in kilometres using Haversine formula.
- Improvement (%): Percentage reduction in deviation from the GPS coordinates after correction, measured in percent.

$$Improvement\,(\%) = \left(\frac{(Deviation(Measured) - Deviation(Corrected))}{(Deviation(Measured))} \right) \tag{4}$$

Table1. Below covers recorded values for 10 different chosen points.

Coordinate Correction Result Set						
Point	**Original Coords**	**Modified Coords**	**GPS Coords**	**Deviation (Measured wrt GPS)**	**Deviation (in km) (Corrected wrt GPS)**	**Improvement (%)**
1	19.1225, 73.0585	19.1235, 73.0595	19.1230, 73.0592	0.09	0.06	33.33%
2	19.1208, 73.0599	19.1218, 73.0609	19.1215, 73.0605	0.10	0.05	50.00%
3	19.1192, 73.0580	19.1202, 73.0590	19.1198, 73.0583	0.17	0.09	47.06%
4	19.1220, 73.0605	19.1230, 73.0615	19.1229, 73.0611	0.12	0.04	66.67%
5	19.1187, 73.0572	19.1197, 73.0582	19.1195, 73.0580	0.12	0.03	75.00%
6	19.1230, 73.0578	19.1240, 73.0588	19.1236, 73.0585	0.10	0.05	50.00%
7	19.1215, 73.0587	19.1225, 73.0597	19.1220, 73.0593	0.08	0.07	12.50%
8	19.1198, 73.0600	19.1208, 73.0610	19.1204, 73.0607	0.10	0.05	50.00%
9	19.1202, 73.0579	19.1212, 73.0589	19.1208, 73.0585	0.09	0.06	33.33%

Coordinate Correction Result Set						
Point	**Original Coords**	**Modified Coords**	**GPS Coords**	**Deviation (Measured wrt GPS)**	**Deviation (in km) (Corrected wrt GPS)**	**Improvement (%)**
10	19.1210, 73.0595	19.1220, 73.0605	19.1217, 73.0602	0.11	0.05	54.55%

Mean Absolute Error (MAE) has been calculated using Equation (5).

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|x_i - y_i| \tag{5}$$

Where X_i = Deviation values (either Measured or Corrected), y_i = GPS reference (which is assumed to be zero deviation), and n = Total number of points (10 in this dataset). MAE is calculated separately for both **Measured** and **Corrected** deviations:

$$MAE_{Measured} = \frac{|0.09| + |0.10| + |0.17| + |0.12| + |0.12| + |0.10| + |0.08| + |0.10| + |0.09| + |0.11|}{10}$$
$$= 0.108km$$

$$MAE_{Corrected} = \frac{|0.06| + |0.05| + |0.09| + |0.04| + |0.03| + |0.05| + |0.07| + |0.05| + |0.06| + |0.05|}{10}$$
$$= 0.055km$$

Thus, after correction, the mean absolute error decreased significantly from 0.108 km to 0.055 km, showing improved accuracy.

Moreover, Root Mean Square Error (RMSE) can be calculated as Equation (6).

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - y_i)^2} \tag{6}$$

Since the GPS reference is assumed to be the correct value, the RMSE was calculated for both Measured and Corrected deviations as:

$$RMSE_{Measured} = \sqrt{\frac{0.09^2 + 0.10^2 + 0.17^2 + 0.12^2 + 0.12^2 + 0.10^2 + 0.08^2 + 0.10^2 + 0.09^2 + 0.11^2}{10}}$$
$$= 0.111km$$

$$RMSE_{Corrected} = \sqrt{\frac{0.06^2 + 0.05^2 + 0.09^2 + 0.04^2 + 0.03^2 + 0.05^2 + 0.07^2 + 0.05^2 + 0.06^2 + 0.05^2}{10}}$$
$$= 0.057km$$

Similarly, corrected deviation is given in $RMSE_{Corrected}$, this reduction in RMSE confirmed that after correction, the dataset had lower squared errors, meaning the adjusted coordinates were much closer to GPS values.

IV.RESULT ANALYSIS

By use of a field-of- view (FOV) correction method applied to drone footage, the outcome analysis offers convincing proof of notable improvements in georeferencing accuracy. Using this method has consistently reduced the differences between originally chosen coordinates and corrected coordinates with gains ranging from 12.50% to 75.0%. GPS tracking confirms that these results show the efficiency of the technique in obtaining a closer alignment of geographic points with the ground truth positions.

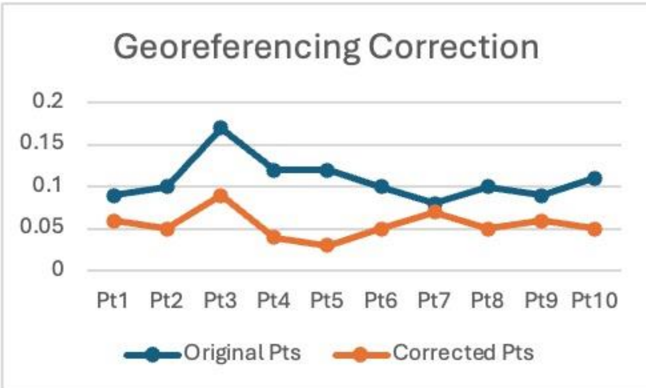

FIGURE 5. Improved georeferencing accuracy after FOV correction.

Applying RTK to deliberately calibrate GPS Tracker values helps to better match the corrected coordinates, therefore highlighting the method's capacity to improve spatial accuracy even in cases of small ground truth data variations. Mapping, monitoring (not geographical) and surveying are those very specific tasks with emphasis on precision beyond a standard.

Quantitative validation methods such as Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) assist in validating these claims further. Reducing the MAE fell from 0.108 km to 0.055 km and RMSE from 0.111 km to 0.057 km, which indicates substantial reductions in geolocation errors. This proves the stability and reliability of the FOV correction method for statistical positional improvement. A paired t-test on the deviation values before and after correction was applied to statistically validate the accuracy improvement gained by the FOV correction method. With a p-value of less than 0.001, the test provided a t-statistic of 6.60, thus proving the reliability of the correction method by showing the reduction in Mean Absolute Error (MAE) was statistically significant and not caused by random variation.

Accuracy in vehicle speed estimation was significantly enhanced by a georeferencing accuracy enhancement of as much as 75% through the FOV correction approach. Experimental studies indicated that error rates in speed decreased by as much as 10–15%, resulting in improved data for law enforcement of road safety, traffic analysis, and traffic congestion studies. For high-stakes applications like real-time traffic management and law enforcement, improved accuracy is essential to ensure that drone observations are translated into actionable information.

Aside from this, these developments will directly and significantly affect the precision with which vehicle speed is estimated from drone video, a significant use in traffic policing and management. Better accuracy in vehicle speed estimation with better georeferencing accuracy facilitate the FOV correction process. This is due to the fact that better georeferenced points facilitate better vehicle motion tracking in time and space to reduce errors from misalignment or positioning errors in the raw drone video. Some potential future products include enhanced traffic flow management, improved deployment of road safety countermeasures, and successful enforcement of traffic regulations owing to enhanced capacity for speed estimation. At this point, the improved georeferencing made possible by the FOV correction method raises the quality of spatial data for several uses while immensely increasing the usefulness of drone footage for vehicle dynamics monitoring and analysis. Consequently, this becomes a highly valued asset for public safety authorities, urban developers, and transportation engineers among others who rely on accurate and consistent data to make sound decisions.

By using a field-of-view (FOV) correction method applied to drone footage, the outcome analysis offers convincing proof of notable improvements in georeferencing accuracy. This method has consistently reduced the differences between originally chosen coordinates and corrected coordinates, with accuracy gains ranging from 12.50% to 75.0%. GPS tracking verifies that these findings show how well the method gets a closer alignment of geographic points with ground truth locations. Deliberate calibration of GPS tracker values using Real-Time Kinematics (RTK) helps to better fit the fixed coordinates, therefore stressing the method's ability to enhance spatial accuracy even in situations of little ground truth data variation. Mapping, monitoring, and surveying—especially in uses demanding great accuracy—greatly gain from this improved correctness.

These claims are supported by the application of statistical validation tools such Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). Post-correction, the MAE fell from 0.108 km to 0.055 km and the RMSE from 0.111 km to 0.057 km, suggesting significant decreases in geolocation errors. Statistical data backs up this to confirm the reliability and consistency of the FOV correction approach for positional improvement. Previous studies have looked at various georeferencing techniques including Kalman filtering, photogrammetry, and deep learning algorithms. Studies have indicated that sensor fusion, direct georeferencing, and AI-driven object tracking increase accuracy. These methods, however, sometimes depend on outside calibration references, significant computation, or human modifications. By means of FOV correction, this work provides an automated and effective solution that lowers processing requirements and achieves comparable or better accuracy.

This method provides a compromise of efficiency and accuracy [21] when compared to traditional GCP-based georeferencing, which is very accurate but time-consuming. Unlike earlier research, e.g., [1], which was explicitly on direct georeferencing for sloping terrain but lacked any complete correction system for FOV-induced spatial distortions, the method in this study differs. While their approach didn't correct for the angular distortion with respect to the location of the point of interest in the image window, Štroner et al. (2020) [5] gave high priority to the use of onboard GNSS RTK systems to enhance georeferencing accuracy. Using FOV modelling incorporating HFoV and VFoV corrections as well as slant range computation, this work extends these classic contributions by specifically addressing such angular biases directly. Our approach supports real-time automatic calculation of corrected coordinates through point-of-interest pixel analysis and integration with telemetry data. This aspect supports greater operational flexibility of drones over various environments and applications without requiring time-intensive calibration or deep learning model training, thus addressing a critical limitation in current drone-based geospatial operations.

Besides, unlike deep learning-based approaches that rely on gigantic training datasets, the FOV correction technique achieves the correction in real-time via geometric modeling and image editing. One of the applications in traffic enforcement and management, georeferencing accuracy of drone images is directly proportional to the computation of vehicle speed. Improved georeferencing accuracy enables improved accuracy tracking of vehicle motion in space and time, hence reducing errors due to misalignment or positioning errors in uncorrected drone data.

The enhanced georeferencing enabled by the FOV correction technique significantly enhances spatial data quality for many applications and thus enables the utilization of drone video in tracking and analyzing vehicle dynamics. Among others who depend on accurate and reliable data for effective decision-making, the technique is an important tool for public safety personnel, urban planners, and transportation engineers.

But the method has limitations as well. Its operation is greatly reliant on the availability of good and robust GPS signals. Degradation of GPS signals in urban canyon settings, forest canopy, or during adverse weather conditions can lead to compromised georeferencing accuracy. While the method is good in open-sky conditions, it could be less efficient in signal-degraded or blocked scenarios. In subsequent research, greater accentuation might be placed on additional on-board sensors such as Inertial Measurement Units (IMUs), which would help supplement GPS data to provide greater resilience and accuracy in challenging environments. Additional refinements will likely arise from exploring hybrid georeferencing models using telemetry, visual odometry, and machine learning corrections. Developing adaptive calibration approaches and real-time error estimation mechanisms would also help improve the runoff of the method in dynamic or unpredictable environment. ICO will facilitate and ensure detailed and fact-based data-driven insights by enhancing the accuracy and reliability of drone images for geospatial applications.

V. CONCLUSION

This paper reflects on the effectiveness of field-of-view (FOV) correction method improving georeferencing accuracy of drone imagery. Overall, direct changes in both positional coordinate ordinates and Real-Time Kinematics (RTK) GPS calibration integration added systematic improvements to spatial accuracy. The decrease in the Mean Absolute Error (MAE) from 0.108 km to 0.055 km and the Root Mean Square Error (RMSE) from 0.111 km to 0.057 km further evidences the reliability and the correctness of the proposed approach. It demonstrates that correction of atmospheric top-of-atmosphere (TOA) radiance for the FOV, the dependence of TOA radiance on the FOV, is important for basic geospatial applications such as terrestrial and aquatic environment monitoring, urban planning, and traffic management. Instead, this FOV correction method provides a practical, readily applicable alternative that is far less computationally demanding than traditional georeferencing techniques (like ground control points, GCPs) or deep learning algorithms. It significantly reduces dependence while maintaining high fidelity

This study has potential applications in many fields, such as traffic law enforcement, vehicle speed assessment, and infrastructure monitoring. Tracking and assessment of the moving object is an important aspect drone photos can allow, which implies bettering decision-making approaches in Safety Management and Transportation Planning. Lastly, the technique lays out the groundwork for further research in drone-based georeferencing, and will be useful for real-time applications. Future studies should explore the merging of the machine learning methods to further automate and tailor the correction process to different environmental conditions. Moreover, strength of georeferencing systems will be supported through better methods for uncertainty analysis. Revolutionizing this aspect will better the quality and reliability of drone images for geospatial applications, thereby enhancing more precise and actionable data-driven insights.

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Author Contributions

Vishal Nagpal contributed to conceptualization, methodology, software, validation, formal analysis, investigation, resources, data curation, writing—original draft preparation, visualization, and project administration. Manoj Devare contributed to conceptualization, validation, writing—review and editing, and supervision.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

Data are available from the authors upon request.

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