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AI-Assisted Thermal Mapping for Predictive Maintenance of Urban Heating Pipelines

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Abstract – **Monitoring hot water infrastructure in cities is vital for sustainability. This study uses drone-based thermal imaging and Python algorithms to detect anomalies. Geo-coordinates of hot spots are mapped into a GIS system. Results show clear links between thermal patterns and infrastructure condition, aiding smarter, safer urban management and planning.**

Keywords: **uav, correlations, prediction, thermal distribution, thermal imaging, underground district heating infrastructure**

I. Introduction

Thermal mapping is an innovative and efficient technique, widely used in a variety of industries, including energy, construction, agriculture, and urban planning. This technique brings a number of advantages that significantly contribute to the efficiency and safety of operations. Thermal mapping enables quick and accurate detection of problems such as leaks in the hot water network, overheating of equipment and weaknesses in insulation, detection of urban heat islands, etc. Also, this method improves energy efficiency in buildings, enabling the identification of places where heat loss occurs, thus achieving significant savings in heating and cooling costs, etc. [1]. From the point of view of the development of smart cities, thermal mapping is an indispensable technology that contributes to sustainability, efficiency and improvement of the living standards of citizens. This technique allows for precise analysis of temperature "*patterns*" in urban environments, which helps to identify and solve problems related to energy, infrastructure, and the environment [2]. In the context of smart cities, thermal mapping is used to optimize energy consumption, reduce CO2 emissions, and improve urban planning, thus contributing to the overall goal of creating sustainable and greener cities [3].

Geographic Information Systems (GIS) play a key role in the development of smart cities by enabling the analysis and visualization of data that is essential for infrastructure management, urban development planning, and sustainable mobility. By using GIS, local governments can monitor the condition of road infrastructure, water supply systems, hot water systems, and air quality, which helps to make important management decisions [4 -6].

GIS also facilitates citizen participation in the planning process, enables more efficient management of resources and improves the quality of life, thus contributing to the development of more resilient and sustainable urban nvironments [6]. This paper presents the results of thermal mapping of selected locations in the City of Nis to monitor the condition of the hot water infrastructure and detect network failures. In addition to conventional tools, this paper develops and applies an advanced Python algorithm for automatic detection of thermal anomalies using machine learning (ML) techniques and basic image processing. OpenCV, scipy.ndimage, GeoPandas, Shapely, Matplotlib, and Fiona have been implemented to find cluster hot spot centers on raster thermal imagery [8-15].

II. Methodology

The thermal mapping process involves several key steps that are essential for its effectiveness. The first step is to define the area to be recorded, as well as identify potential problems or places of interest. This step also involves analyzing previous data, as well as consulting with experts to determine the areas with the highest risks or inspection needs. In this step, the appropriate devices and equipment are also selected, including thermal cameras and analytical software for data processing. Data collection includes the use of these cameras, which generate thermal images of objects and spaces, detecting the thermal radiation emitted by them [10].

In the next step, the thermal images were imported *into the DJI Thermal Analysis Tool*, where they were displayed in high resolution, with each pixel associated with temperature information. Different temperature palettes are used to visualize temperature differences in a clearer way, highlighting heat sources and areas with increased losses. Then, tools were used to accurately measure the temperature at selected points in the image or along lines that spanned specific segments of the heat pipe. Analysis of these measurements made it possible to identify points with unusual temperatures that could indicate potential failures. Also, *the DJI Thermal Analysis Tool* provided the ability to apply isoterm filters, which visually highlighted certain temperature ranges, allowing the team to quickly identify areas that require additional attention [7].

After identifying problem points, reports were generated directly from the software, including images with temperature labels and temperature data for each marked area. These reports were later used to further assess the condition of the hot water system and plan maintenance. *The DJI Thermal Analysis Tool* has significantly simplified the analysis, allowing the team to process data accurately without the need for additional tools or software.

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For each anomaly detected, precise geo-coordinates were calculated, which were then filtered based on the distance from the hot-water route (LineString) to eliminate false positives outside the infrastructure line. All data is then exported in a standardized format. GPG format, with an additional. PGW files for direct loading of PNG rasters into QGIS. In this way, full GIS integration is provided, including layers with thermal anomalies, heat pipe lines, and raster image layers.

This methodology allows for automatic and scalable analysis of a large number of thermal images using artificial intelligence, without the need for manual review. Potential for expansion also includes the use of deep convolutional networks (CNNs) to classify leakage patterns and predict failures in future phases of research.

III. RESULTS &DISCCUSION

After entering the data, the software ran the processing steps, Initial Processing for image orientation and point determination, then Point Cloud and Mesh to generate point clouds and 3D models, and finally DSM, Orthomosaic and Index to create orthophotographic representations. The first step generated a 2D orthophotomap from RGB images, while for the thermal display, the software used thermal camera data, allowing the visual and thermal state of the surface to be compared.

The integration of *the PIX4D* orthophotomosaic into Google Earth Pro was a useful procedure for the visualization and analysis of geoinformation. First, PIX4D finished processing the data to generate the orthophotomosaic, and then the georeferenced TIFF file was exported. After that, in Google Earth Pro, the "Add" option is activated and "Image Overlay" is selected to load the orthophotography. The layer name and the selected file are set, and then the move and size tools are used to place the image in the appropriate location on the map. It was important to check that the orthophoto was properly georeferenced and aligned with other layers in Google Earth. Once the settings were complete, the layer could be saved and shared as a KML or KMZ file, allowing for easy exchange of information with other users.

This process has not only improved spatial data analysis but has also facilitated informed decision-making and understanding of complex urban and natural environments.

The thermal layer imported into Google Earth Pro is a visualization of the intensity of thermal radiation within the hot water network, enabling effective monitoring of the condition of the underground infrastructure. This visualization helped operators quickly identify potential problems, which was crucial for further analysis steps.

The images mark critical points and others that indicate places of increased thermal radiation intensity in important parts of the system. These points are especially analyzed in *the DJI Thermal Analysis Tool* environment, with multiple aspects.

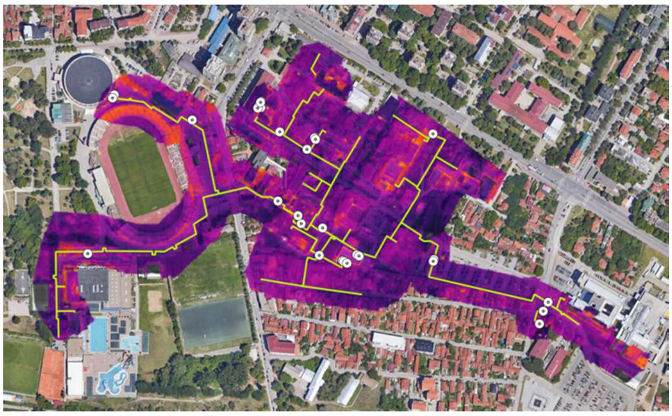

Figure 1. Thermal map in Google Earth pro

Fig. 1 shows the thermal map visualized in Google Earth Pro, highlighting the intensity of thermal radiation along the heating pipeline.

In this way, the integration of the thermal layer into geoinformation tools such as Google Earth Pro makes it possible to improve the monitoring and maintenance of the system.

An automated, machine learning-based system was also developed using Python scripts (scipy.ndimage, shapely, and geopandas) to identify and cluster thermal anomalies directly from PNG thermal layers (see Fig. 2). The model for predictive analysis utilized a multi-layer perceptron (MLP) regressor implemented in scikit-learn, with typical parameters such as hidden_layer_sizes=(64, 32), activation function set to 'relu', and a learning rate of 0.001 [12, 13]. Only detections within a 5-meter radius of the pipeline were retained as valid, significantly reducing the number of false positives. This method replaces manual tagging and enables faster, more accurate, and consistent detection of critical points in a GIS environment. The detected points were then visualized in QGIS (Fig. 2), and overlaid on a street map for context (Fig. 3).

The critical points identified in this way are not only visually isolated but are the result of a combined treatment, first with a thermal sensor, then with automatic vectorization and spatial pairing through deep learning algorithms that identify patterns characteristic of heat leaks and losses.

Purple and yellow hues on the thermal layer indicate temperature differences; purple indicates cooler areas, while yellow represents warmer spots that indicate potential sources of energy loss or heat leakage in the hot water system. By analyzing this layer in the *DJI Thermal Analysis Tool* environment and analyzing the *Google Earth Pro* map, critical points in the network were identified. Using such a layer in an environment such as Google Earth Pro makes it easier to track and analyze data in the context of the actual geographic environment, thus improving the overall management of the hot water system.

Critical hotspots during filming, hot spots pose a potential hazard, as they can increase the risk of corrosion or other damage to the pipeline. Also, by modeling the heat distribution, we can determine the optimal insulation thickness for the pipeline, which can help reduce heat loss and improve the efficiency of the pipeline. By predicting the lifespan of a pipeline, we can identify parts that are likely to require repairs or replacement before they can be replaced. This approach can help plan for pipeline maintenance and repairs, which can minimize service disruption and ensure that the pipeline is operating safely and efficiently.

As part of this research, an algorithm for estimating long-term stability based on thermal parameters was also developed, using a deep learning regression model approach (e.g., MLP regressor from sklearn) that was trained on simulated material degradation data depending on the intensity and duration of temperature anomalies. The MLP regressor was implemented using the scikit-learn library with the following hyperparameters: hidden_layer_sizes = (64, 32), activation = 'relu', solver = 'adam', learning_rate_init = 0.001, and max_iter = 500. These settings were chosen based on preliminary grid search experiments to balance accuracy and computational cost. This enables not only detection but also prediction of the duration and severity of potential failures, which further improves preventive maintenance [13, 16]. Also, automatically generated .pgw files enabled precise positioning of PNG thermal layers in QGIS, creating a direct bridge between machined images and GIS vector infrastructure layers. This allows for synchronized visualization of all data in a single system.

In addition, georeferencing helps reduce the risk of damage and leaks by tracking changes over time, which is crucial for preserving the environment. Connecting to other systems, such as water and sewage, improves the overall management of the infrastructure, while increasing transparency towards citizens and decision-makers. In today's smart cities, georeferencing is essential for the sustainability and efficiency of urban systems.

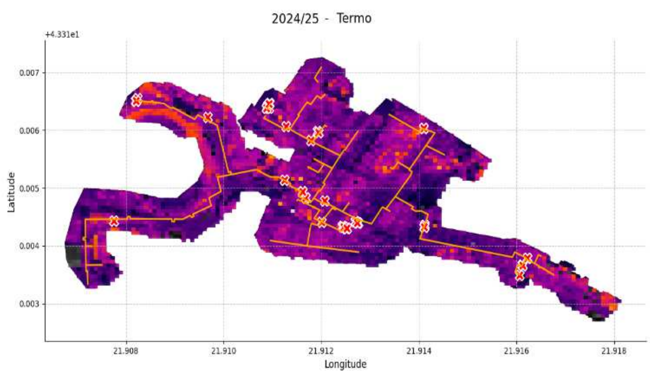

Figure 2. QGIS map of critlac points

As presented in Fig. 2, the QGIS environment displays all detected critical points, facilitating geospatial analysis and further decision making.

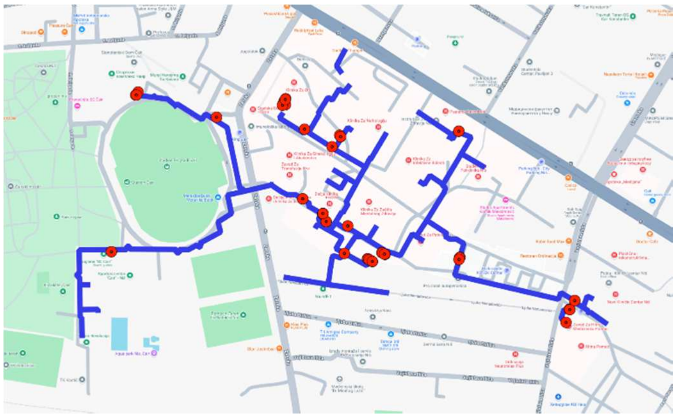

Figure 3. Regular street map with critlac points

Fig. 3 illustrates the locations of critical points superimposed on a standard street map for easier contextual interpretation.

IV. Conclusion

This paper presents a comprehensive approach to monitoring underground district heating infrastructure using UAV-based thermal imaging, geospatial analysis, and machine learning. By integrating drone-captured thermal data with GIS tools such as QGIS and Google Earth Pro, the system provides accurate detection and localization of heat anomalies, indicating potential infrastructure failures. The use of Python-based image processing and anomaly detection scripts allows for automated and scalable identification of critical zones. Additionally, predictive modeling using deep learning techniques enhances the ability to forecast the severity and progression of infrastructure degradation. This interdisciplinary methodology supports proactive maintenance, energy efficiency, and the sustainable development of smart cities. Future work will focus on refining deep learning models and integrating real-time monitoring capabilities.

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