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Reading Urban Heritage Through Roofscapes: A Machine Learning Approach for Tirilye

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Abstract

Historic towns often lack thorough records, complicating the study of long-term material changes in the built environment. This study develops RoofChronoNet, a machine learning workflow that extracts roof covering classes from grayscale imagery and quantifies roofscape change over time. Applied to Tirilye (Bursa, Turkey), historical aerial photographs from 1970 and 1984 are colourised using a pix2pix generative adversarial network trained on 2022 imagery. A YOLOv11m-seg model then detects roof surfaces and classifies them into three roof covering categories: red, white, and dark grey, producing diachronic roofscape maps for 1970–2022. Bounding box detection reached mask mAP@0.50 of 0.81 (2022), ≈0.71 (1984), and 0.76 (1970, single class), while class-averaged mask mAP@0.50 was lower due to pixel-level delineation complexity. Results indicate the persistence of red-tiled roof regimes within the historic core alongside a growing presence of white and dark-grey roof coverings in peripheral areas, consistent with renovation-driven material diffusion after the 1980s. Methodologically, the study contributes a reproducible framework that operationalises chromatic differentiation as a measurable variable for mapping roof covering regimes in planning history research using monochrome historical aerial imagery. RoofChronoNet supports heritage-oriented and planning history interpretations of material regime shifts in data-scarce contexts; however, colourised outputs are synthetic and probabilistic, and spatial inferences should be corroborated with archival or field-based evidence where feasible.

Keywords: historical aerial imagery; machine learning; roofscape analysis

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1. Introduction

Understanding the evolution of urban morphology is a crucial aspect of planning history, especially in historic towns where physical changes often occur gradually and outside the framework of formal planning documentation. In such contexts, the physical fabric of the city (its streets, facades, and roofscapes) provides a durable record of continuity and transformation. Roofscapes illustrate construction technologies, maintenance practices, material economies, and cultural preferences, making roof colour and roof covering classes valuable yet underexplored indicators of material regime change and renovation phases observable in historical aerial imagery.

From an aerial perspective, chromatic differentiation contributes to the perceptual legibility of urban history at settlement scale. Persistent roof colour concentrations register

long-term material continuity, whereas chromatic diversification may indicate renovation cycles, regulatory shifts, or changing construction economies. Roof colour is therefore approached not as a symbolic repository of collective memory but as a visually traceable layer through which material transformation becomes spatially perceptible in historic urban fabrics.

The study focuses on Tirilye, a coastal town in Bursa Province, northwestern Turkey, designated as an urban conservation area. Tirilye presents a historically layered settlement with Byzantine and Ottoman architectural heritage, a preserved street pattern, and a dense core of registered historic buildings. As in many Mediterranean heritage contexts, cadastral and registry records in Tirilye are incomplete, while recent redevelopment pressures have accelerated material changes, especially in roofing. Historical aerial imagery reveals a shift from predominantly red-tiled roofs to an increasing share of white and dark-grey roof coverings associated with contemporary construction and renovation practices.

While urban morphologists have long used historical maps and field surveys to analyse change, integrating high-resolution aerial imagery with advanced computer vision and machine learning techniques offers new opportunities for planning history. However, few studies have systematically employed roof colour as a temporal indicator, and even fewer have done so by combining generative image translation and automated segmentation to build a diachronic dataset.

Nevertheless, conventional urban morphological research has provided strong analyses of street networks, plot systems, and building typologies, yet it often relies on two-dimensional sources such as cadastral maps and figure–ground representations [1–3]. These materials capture spatial configuration effectively, but they offer limited leverage for examining three-dimensional material attributes that shape the townscape's visual character, including roof covering regimes and chromatic variation. Remote-sensing imagery can register surface colour and texture; however, long-term historical continuity is uneven across datasets. High-quality colour imagery is typically available only for recent decades, whereas earlier aerial archives are predominantly monochrome, constraining long-term diachronic comparability [4–6].

Existing literature shows that urban morphology provides a robust framework for interpreting the temporal layers of the built environment. Remote sensing and GIS techniques are used to analyse the temporal and spatial dimensions of urban morphology. Changes in urban form, differences in density, and morphological patterns are examined using high-resolution images [7–9]. Recent studies have shown that roof coverings and colours are important indicators of urban typology, energy consumption, and socioeconomics. Detecting roof materials from high-resolution multispectral images offers new opportunities for urban sensing and planning [10]. The separation of roof colours using spectral indices with Sentinel-2 data has revealed the effects of coloured roofs on urban sustainability and energy balance [8]. However, roofscapes, particularly roof colours, are rarely considered primary evidence in planning history studies. In historic cities, where official cadastral data is often incomplete, neglecting roofscapes limits the variety of accessible temporal indicators of material change. Long-term visual records from aerial photographs and satellite imagery have enabled tracking of urban change over decades. Examples include Demiröz and Güçhan's [11] study, which analysed spatial changes in the Ankara Acropolis in Turkey by utilising historical maps and aerial photographs; Filepné Kovács [12] examination of the historical evolution of the urban green network in Veszprém through cadastral and topographic maps; Gheitasi, Maddahi and Salari's [13] analysis of rapid urban growth in Birjand using satellite imagery; and Alacam et al.'s [14] study, which employed a CycleGAN-based machine learning framework to enable reciprocal style

and information transfer between the historical Istanbul Pervititch Maps (1922–1945) and contemporary satellite views.

In heritage frameworks, roofscapes are also treated as components of the visual integrity of historic urban landscapes. Rapoport [15] argues that dwelling form is shaped not only by climatic and environmental constraints but also by social values and culturally embedded notions of appropriate construction. Roof forms and roof covering materials can be read as part of a historically situated material culture. Similarly, Rudofsky [16] emphasises that in vernacular architecture, the roof evolved as an integral part of local materials, topography, and construction traditions. Heritage conservation frameworks also emphasise the role of roofscapes in sustaining the legibility of townscape character [17]. Accordingly, chromatic and material variation visible in aerial imagery is treated here as an indicator of material regimes and conservation or renovation conditions at the time of image acquisition, rather than as evidence of original construction chronology.

The study of urban form—how settlements are structured, grow, consolidate, and transform—is a core concern of planning history. Morphological approaches, which originated in the Conzenian tradition and have since been developed in various contexts, rely on cadastral records, cartographic archives, and field surveys to interpret the evolution of the built environment [18–20]. Heritage towns, particularly in non-Western and post-Ottoman contexts, offer analytically productive settings for morphological research, where documentary gaps make the built fabric a primary source of evidence.

Over the past two decades, Geographic Information Systems (GIS) have become indispensable in advancing morphological research by enabling the integration of historical maps, archaeological surveys, and archival records into spatial–temporal analyses [21–23]. GIS-based approaches have proven especially valuable in heritage settings where rapid urbanisation threatens the historical fabric. Nevertheless, methodological challenges persist. Differences in scale, projection, and data quality complicate source integration, and few approaches successfully bridge empirical mapping with computational modelling in a manner transferable across historical contexts [24,25].

Roofscapes remain comparatively under-examined despite their potential to indicate material change. Roof characteristics such as form, pitch, and colour are widely recognised as markers of architectural identity and components of the historic urban landscape [26]. In Mediterranean and Anatolian towns, red terracotta tiles historically dominated due to local clay availability and artisanal production, while the increasing presence of white and dark-grey coverings reflects industrialised materials, renovation cycles, and post-1980 modernisation processes. Although international studies have examined roofscapes in relation to visual integrity, cultural landscape management, and heritage tourism [27,28], research in Turkey has largely remained qualitative, with limited systematic or diachronic classification of roof covering change.

Historical aerial photography and satellite imagery provide long-term visual archives that can partially compensate for missing cadastral and planning records. From post-war aerial surveys to medium-resolution satellite datasets such as Landsat, sources have been widely used to analyse urban growth and land-cover change [29,30]. High-resolution monochrome imagery, including declassified CORONA photographs, offers particularly valuable records of historic urban fabrics prior to large-scale modernisation [31,32]. However, the predominance of greyscale imagery limits the interpretation of colour-sensitive roof covering signals relevant to material regimes and renovation processes.

Recent advances in computer vision and machine learning offer new opportunities to address the limitation. Generative models such as Pix2Pix can produce plausible chromatic representations from grayscale imagery [33], while segmentation algorithms enable the automated detection and classification of roof surfaces [34]. Although widely applied in

contemporary urban monitoring, the combined use of colourisation and segmentation for heritage-oriented morphological analysis remains rare. Integrating the techniques offers a replicable means of generating diachronic roofscape datasets that bridge visual interpretation and quantitative mapping.

Taken together, research indicates an analytical gap. Urban morphology provides robust tools for interpreting planimetric structure; remote sensing enables surface classification and land-cover detection; and heritage theory emphasises visual integrity and material continuity in historic urban landscapes. Yet few studies integrate these approaches into a reproducible framework for diachronic mapping of roof covering colour classes, particularly when historical aerial archives are predominantly monochrome. The absence of such a framework constrains the systematic use of roof covering regimes as comparable planning history indicators across long temporal horizons. The present study is intended to address this methodological gap through the RoofChronoNet workflow.

Against this background, the study develops and applies RoofChronoNet, an integrated workflow combining GAN-based colourisation and automated roof segmentation, to analyse roofscape transformation in Tirilye, a historic coastal town in northwestern Turkey with incomplete archival documentation. By mapping the spatial and temporal distribution of roof covering classes between 1970 and 2022, the study demonstrates how roofscapes can be interpreted as indicators of material regime change and renovation phases, contributing a methodological framework for digital planning history and heritage monitoring.

The study investigates how visual features embedded in roofscapes—particularly roof colour and roof covering classes—can support the interpretation of the built environment's transformation in Tirilye, Bursa. The research explores the intersection of historical analysis and digital methodology in a context where conventional architectural records are incomplete. The following core aims guide the research:

- Assess the feasibility of extracting roof covering classes from grayscale historical aerial imagery by using a combined colourisation and segmentation workflow in historic urban settings with limited archival documentation.
- Develop RoofChronoNet as a reproducible pipeline for roof detection, roof covering classification, and diachronic roofscape mapping, and apply it to analyse spatio-temporal roofscape transformation in Tirilye between 1970 and 2022.
- Evaluate model performance, limitations, and interpretive uncertainty associated with colourised imagery and AI-based segmentation and specify how archival and field evidence can complement and strengthen computational interpretations in heritage-oriented planning history research.

The study addresses the gap by developing and applying a two-stage computational workflow, RoofChronoNet, which comprises: (1) colourisation of grayscale historical aerial imagery using a pix2pix conditional GAN trained on contemporary imagery, and (2) detecting and classifying roof covering classes over five decades with a YOLOv11m-seg segmentation model. By mapping the spatial and temporal distribution of red, white, and dark grey roof classes from 1970 to 2022, RoofChronoNet reconstructs diachronic roofscape layers that inform the interpretation of Tirilye's morphological transformation. The analysis situates the observed roofscape changes within wider planning and heritage conservation debates. RoofChronoNet constitutes a methodological framework for digital planning history and provides a practical tool for heritage monitoring in towns where the physical record is a primary source of urban history.

2. Materials and Methods

This study introduces RoofChronoNet, a methodological framework that integrates historical aerial imagery with computational analysis to extract and classify different

roofscape categories in Tirilye, Bursa. The workflow facilitates the interpretation of spatio-temporal changes in roofscapes, particularly in relation to shifts in material use and phases of renovation. RoofChronoNet integrates two machine learning components, pix2pix for image translation and YOLOv11m-seg for object segmentation, within a spatial and historical analytical design informed by planning and architectural research.

The YOLOv11m-seg model was chosen for its balance between segmentation accuracy and computational efficiency, which is critical for processing high-resolution aerial images under limited hardware constraints [35]. Compared to two-stage detectors such as Mask R-CNN, the single-stage YOLO architecture enables faster inference while maintaining sufficient sensitivity for detecting small-scale urban features such as individual roofs [34].

The workflow is organised into explicit analytical stages so that each computational step aligns with a defined interpretive function in the historiography of urban form. Figure 1 summarises the sequential stages from data acquisition and preprocessing to model outputs and evaluation.

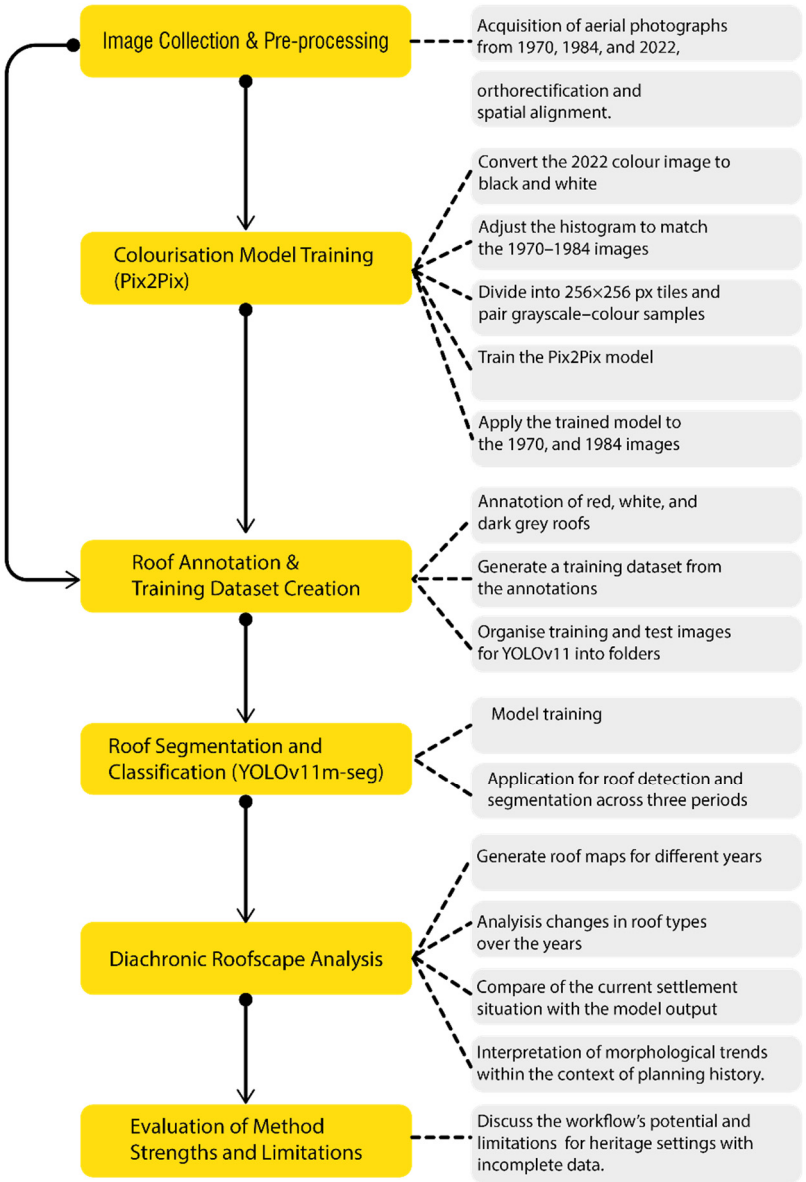

Figure 1. RoofChronoNet workflow steps.

We used three aerial image epochs of Tirilye from 1970, 1984, and 2022. The 2022 map is the only dataset available in full colour, while the 1970 and 1984 maps are available only in grayscale, limiting direct interpretation of colour-related roof covering signals (Figure 2). For pix2pix training, the 2022 colour image was converted to grayscale to generate paired colour–grayscale samples; the workflow therefore uses three primary images and one derived grayscale layer.



Figure 2. Historical aerial maps of Tirilye from 1970–1984 (grayscale), alongside the 2022 colour map used for model training.

We trained a pix2pix conditional generative adversarial network (cGAN) on paired image tiles extracted from the 2022 aerial photograph to generate colourised versions of the grayscale maps. The pix2pix model, introduced by Isola et al. [33], is designed to translate grayscale inputs into synthetic colour outputs based on learned patterns. The original 2022 colour image was converted to grayscale and paired tile-by-tile with its colour counterpart to form a one-to-one training dataset. More than 5000 paired 256 × 256 px tiles were sampled across built-up and natural areas to increase scene diversity and reduce overfitting. Histogram adjustments were applied to align tonal distributions between the 2022 grayscale input and the 1970–1984 imagery, improving cross-period comparability prior to model inference.

All imagery was orthorectified and co-registered to ensure spatial correspondence across decades, enabling diachronic comparison of roof surfaces without geometric distortion. The datasets were projected to the Turkish National Coordinate System (ITRF96/TM30). Orthorectification was performed using ground control points (GCPs) derived from stable urban features, such as street intersections and landmark structures, clearly identifiable across all epochs. A minimum of 20 well-distributed GCPs were used per image to ensure spatial stability.

Images were resampled to a unified ground sampling distance (GSD) of 0.50 m using bilinear interpolation to maintain consistency across temporal layers. Geometric accuracy was evaluated using root mean square error (RMSE), which remained below 1.2 pixels for all datasets, corresponding to a positional error of less than 0.60 m at the working resolution. This level of geometric precision supports reliable diachronic comparison and reduces the likelihood that segmentation outputs are affected by spatial misalignment.

All model training and inference was conducted in Google Colab using an NVIDIA Tesla T4 GPU (16 GB VRAM).

The annotated polygons formed the training dataset for a YOLOv11m-seg model, a segmentation-oriented extension of the YOLO object detection framework. Training was conducted for 100 epochs with a batch size of 16 and an input image size of 256 × 256 pixels. The dataset was divided into 80% training and 20% validation subsets and subsequently converted into YOLO segmentation format. Tiles were sampled across the study area to reduce spatial clustering effects; however, potential spatial autocorrelation between adjacent tiles is acknowledged as a limitation. Given the limited and class-imbalanced

nature of the historical datasets, performance metrics are reported on the validation subset and interpreted as measures of internal consistency rather than indicators of universal model generalisation. The initial learning rate followed the default Ultralytics configuration (lr0 = 0.01). Early stopping and model selection were based on validation mask mAP@0.50 performance. Model inference was performed on the colourised imagery from 1970–1984 and on the original colour imagery from 2022.

Historical images were sourced from the General Directorate of Mapping, Türkiye. Production at a nominal 1:3000 scale for cadastral mapping and urban planning, as part of the 1970s land registration programme, provides a relevant institutional context for the technical standards and planning priorities of that period. The 2022 aerial imagery provides paired colour and grayscale data for training the colourisation model. Our workflow focuses on mapping tonal and textural cues to classify roof covering colour classes. However, it is important to recognise that interpretations are limited to the roof covering patterns that were observable at the time the images were captured, acknowledging that changes may occur due to maintenance and renovation.

Evaluation and limitations

The evaluation examined model performance and spatial interpretability, with emphasis on roof class detection precision and recall and on the consistency of mapped roof covering patterns across space. Visual inspection indicated strong detection of large, visually distinct roof surfaces, while performance declined in densely clustered areas and in zones with lower image quality. Similar sensitivity to resolution constraints and local clutters has been reported in aerial image classification tasks using deep learning. Pix2Pix colourisation generated visually plausible outputs, yet colourised imagery requires critical interpretation in heritage research because synthetic chromatic signals introduce uncertainty that can propagate into roof classification and spatial pattern inference.

Period-specific conditions introduced additional limitations. In the 1970 imagery, the minimal number of white roofs limited class-level evaluation and constrained interpretation primarily to red-tiled roof regimes. Longer building shadows in the 1970 photographs enhanced roof-edge visibility, supporting roof delineation despite overall image degradation. The 1984 imagery contained more white roofs, improving class representation, yet shorter shadows reduced edge contrast for low-rise structures and contributed to segmentation errors. The 2022 imagery, characterised by higher spatial resolution and stronger material differentiation, supported more stable identification of all three roof covering classes and reduced shadow-related ambiguity.

Model design choices also affected outcomes. Training with 256 × 256-pixel tiles often produced partial roof representations, particularly in historical imagery where contextual cues were already limited by degradation. Increasing the tile size to 512 × 512 pixels expanded the spatial context per sample and improved discrimination under low-contrast conditions, reducing fragmentation in roof detection outputs.

Overall, integrating generative colourisation and discriminative segmentation supports the production of diachronic roofscape layers that enable systematic mapping of roof covering regimes at a scale that exceeds manual classification, while maintaining interpretive caution regarding synthetic colour outputs. The workflow offers a transferable methodological approach for heritage-oriented morphological analysis in settings characterised by incomplete building records if uncertainty and class imbalance are explicitly reported and that computational outputs are complemented by archival or field-based evidence where feasible.

The limited number of temporal datasets restricts statistical generalisation, and class imbalance reduces the robustness of inter-decadal comparison. Consequently, the workflow is best understood as an interpretive analytical tool for identifying broad patterns of material change and renovation rather than as a predictive or chronologically precise model.

3. Results

The following section presents the findings generated using RoofChronoNet, which integrates pix2pix-based colourisation and YOLOv11m-seg segmentation with historical aerial photographs of Tirilye. The first part assesses the colourisation stage in terms of producing usable chromatic representations for subsequent classification. The second part reports the outcomes of roof detection and roof covering classification across the analysed time periods.

3.1. Colourisation of Historical Maps

Qualitative assessment indicated that the model translated tonal and textural cues into plausible chromatic approximations in areas with clearer imagery, yet occasional ambiguity and inconsistency occurred in lower-quality regions, especially in shadowed zones and densely clustered blocks. Such artefacts are consistent with limitations reported in GAN-based colourisation of historical imagery and reinforce the interpretive character of model outputs (Figure 3).

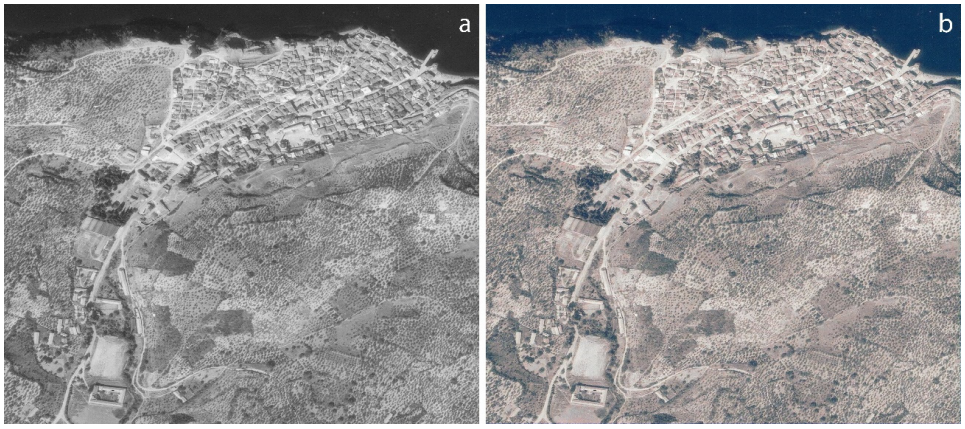

Figure 3. Example of pix2pix colourisation applied to historical imagery. Panel (**a**) shows the original 1970 grayscale tile; (**b**) shows the colourised output.

3.2. Roof Detection and Classification

Following colourisation, roof polygons were manually delineated and labelled on the 1970, 1984, and 2022 aerial photographs using the makesense.ai annotation platform (Figure 4). All annotations were completed by the same researcher to ensure consistency across temporal datasets. To assess intra-annotator reliability, a randomly selected subset of annotated tiles (approximately 10%) was re-annotated after a time interval and compared with the original labels. Minor discrepancies were reviewed and corrected to maintain class consistency across epochs.

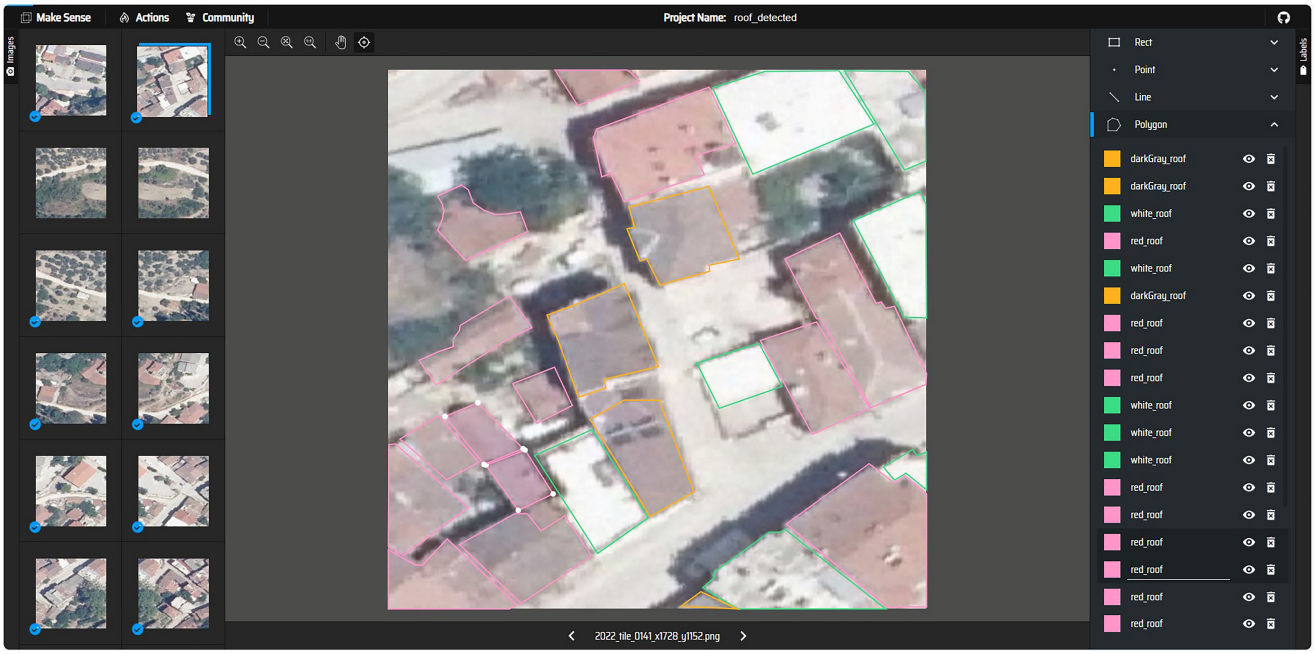

Figure 4. Manual roof annotation process in the Make Sense AI interface. We labelled roof polygons as red (traditional clay tile), white (synthetic/reflective), or dark grey (concrete/modern sheet), categories that correspond to distinct roof covering materials and are commonly associated with different maintenance and modernisation practices in Tirilye. The annotated roof samples formed the training dataset for the YOLOv11m-seg segmentation model. Interface boundary colours are automatically assigned by the annotation platform and correspond to the predefined roof-cover classes.

Each polygon was assigned to one of three roof covering classes: red roof, white roof, or dark grey roof. The classes correspond to roofing materials documented through field observation and archival photographs in Tirilye, where red generally indicates clay tile, white represents reflective or synthetic coatings, and dark grey indicates concrete or modern sheet materials associated with different maintenance and modernisation practices. The annotated roof samples formed the training dataset for the YOLOv11m-seg segmentation model (Figure 4).

Detection and classification outcomes varied by observation period, with higher roof detection rates in imagery characterised by stronger spatial contrast and lower occlusion.

In the 1970 tiles, annotated samples were strongly imbalanced, with 534 red roofs and only 15 white roofs. Given the limited representation of white roofs, training and evaluation proceeded in a single-class configuration restricted to red roofs. Under the configuration, the model achieved a recall of approximately 76% and a precision of 79% (mAP@0.50 = 0.76), indicating reliable identification of dominant, red-tiled roof regimes at an IoU threshold of 0.50. Missed detections were concentrated in compact residential clusters and in areas with faded or overlapping roof textures, while false positives were associated with visually ambiguous structures and partially occluded rooftops.

In the 1984 tiles, red and white roofs were represented by approximately 560 and 52 instances, respectively, enabling training and evaluation in a two-class configuration. Results yielded a recall of approximately 81% and a precision of 40% (mask mAP@0.50 $\approx$ 0.71), indicating improved coverage of annotated roofs but a substantial rise in false positives in denser imagery. Misclassifications clustered around transitions between bright red and faded white roofs; the remaining false positives were linked to ambiguous or partially occluded roof surfaces. Period-specific detection patterns and error types are illus-

trated in Figure 5, which shows representative roof classification outputs for the 1970 and 1984 imagery.

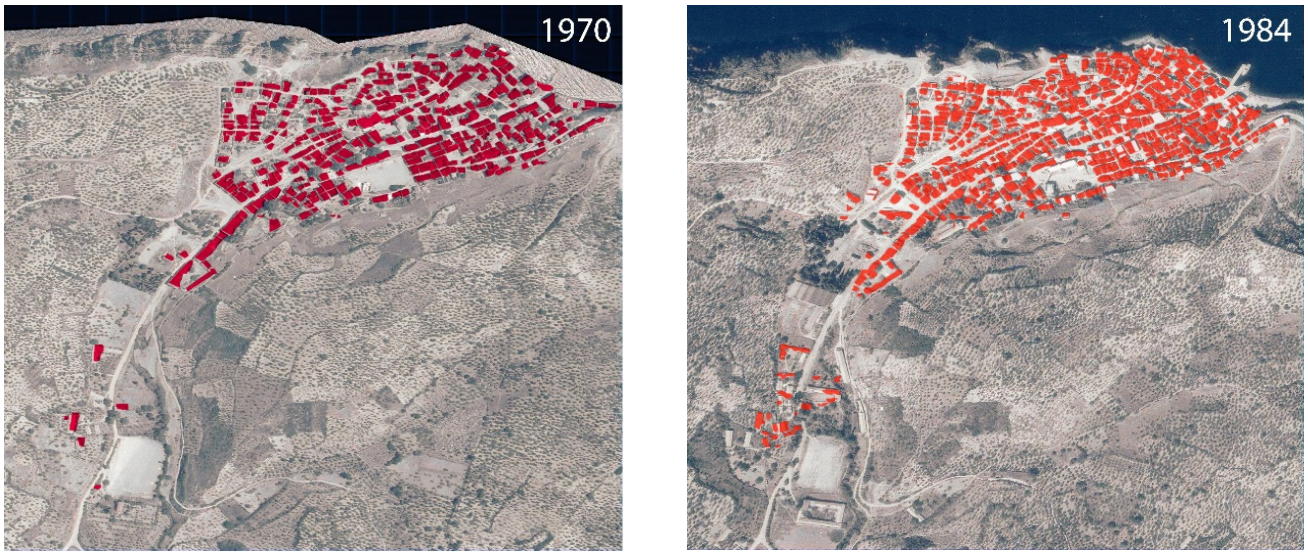

Figure 5. Roof annotation results for the 1970 and 1984 aerial imagery tiles using YOLOv11m-seg, classified as red roofs, white roofs.

In the 2022 dataset, the roof annotations were categorised as red roof, white roof, and grey roof. A total of 869 roofs were identified, comprising 638 red (73.4%), 135 white (15.5%), and 96 grey (11.0%) instances. The model achieved an mAP@0.5 of 0.81, indicating a balanced capacity to differentiate between the three roof types. Recall remained high across classes, while precision showed significant improvements compared to 1984, suggesting that the model was more effective at reducing false positives in contemporary imaging conditions.

Figure 6 presents the mapped roof covering classifications for 1970, 1984, and 2022, with roofs symbolised by red, white, and dark grey categories. The visualisations indicate a persistent concentration of red-tiled roofs within the historic core and a gradual expansion of white and dark grey roof covering regimes in peripheral areas over time. Higher densities of red roofs appear in proximity to the historic bazaar and waterfront, while dark grey coverings are more prevalent in later expansion zones, particularly toward the south and west.

Class-wise evaluation reveals notable performance differences between roof categories. For the 2022 dataset, the red roof class achieved an average precision (AP@0.50) of 0.741, whereas the white roof class achieved 0.373. The overall class-averaged mask mAP@0.50 (segmentation) was 0.557, reflecting the greater difficulty of pixel-level delineation compared to bounding-box detection. This value differs from the higher global detection score reported above due to class imbalance and per-class averaging in segmentation performance, as expected for instance segmentation tasks. Normalised confusion matrix results indicate that red roofs were detected with approximately 0.78 recall and 0.78 precision, while white roofs exhibited lower recall ($\approx$0.39) and precision ($\approx$0.39). This disparity reflects uneven class distribution and greater visual variability in white roof coverings, particularly in transitional or partially occluded conditions. Accordingly, the model is positioned as a spatial screening tool rather than a fully automated material verification system.

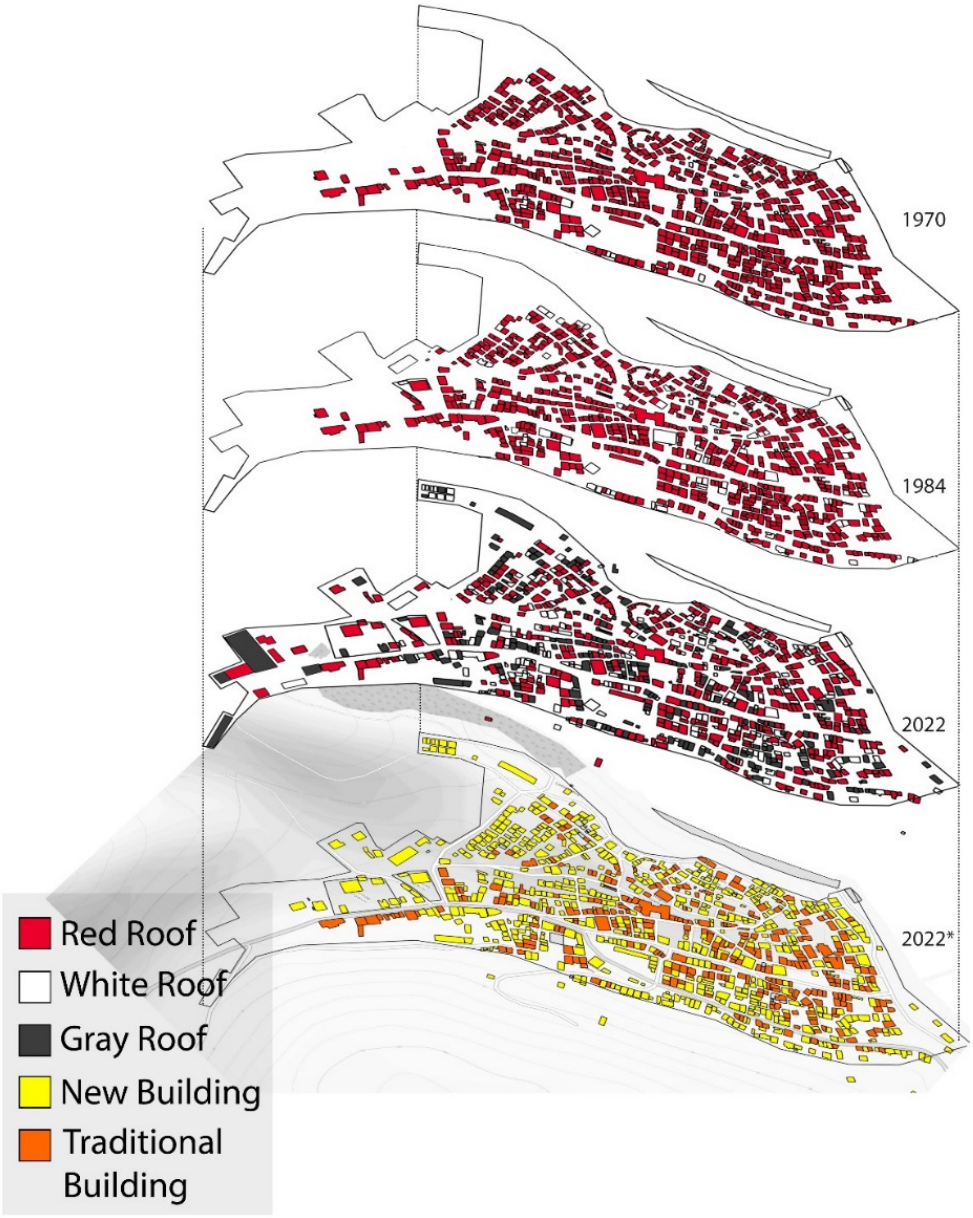

Figure 6. Roof type classifications for Tirilye in 1970, 1984, and 2022, colour coded as red (traditional clay tile), white (synthetic/reflective), and dark grey (concrete/modern sheet). * For 2022, building typology (traditional vs. new buildings) is additionally indicated.

4. Discussion

Following Tirilye's designation as a natural and urban conservation area in 1981, construction and restoration interventions became subject to differentiated regulatory control across the historic core and its surrounding areas. The conservation criteria applied within the central zone, where the majority of registered heritage buildings are located, have helped maintain visual coherence by supporting the continuity of traditional red-tiled roof coverings. Since the 1980s, the growth of tourism and related restoration initiatives has increased the frequency of building maintenance and renovation cycles. In peripheral areas, where regulatory oversight has been comparatively more flexible, renovation processes have allowed greater scope for material substitution. Industrial alternatives such as metal sheet panels or membrane coatings may be associated with lower procurement costs, faster installation, and lighter weight, particularly in non-registered buildings and in areas with less intensive conservation oversight. Roof covering change also unfolds within a local

construction economy, where routine maintenance decisions may be shaped by affordability, contractor availability, and the standardisation of industrial building products.

RoofChronoNet addresses a practical limitation in planning-history-oriented urban morphological research: planimetric sources capture spatial configuration but provide limited leverage for examining material attributes across long historical periods. By integrating generative colourisation with instance segmentation, the workflow enables the extraction of roof covering classes from monochrome historical archives, thereby complementing conventional planimetric analysis with a diachronic material regime layer. The methodological contribution lies in operationalising chromatic differentiation as a measurable variable for comparative mapping rather than in reconstructing historically exact colour states. From an applied perspective, the proposed workflow can support heritage management by functioning as a spatial screening tool. Planners and conservation authorities may use diachronic roof covering maps to identify zones of material change, monitor the expansion of non-traditional roofing materials, and prioritise areas for field inspection. The method enables rapid settlement-scale assessment of material transitions that would otherwise require extensive manual survey. In practice, such outputs could inform maintenance planning, conservation zoning updates, or targeted archival investigation of undocumented alterations.

Interpretation is inherently probabilistic and dependent on image quality and class balance. The colourised outputs are approximations based on models rather than verified historical states. Therefore, conclusions drawn from changes in roof colour or material should be understood as patterns at the settlement scale rather than as determinations at the building level. Accordingly, computational classifications should be treated as decision-support tools rather than as definitive material verification. Our results require corroboration through field survey, archival documentation, or high-resolution imagery before informing regulatory or policy decisions.

5. Conclusions

This research emphasises the analytical value of roofscape evidence for examining long-term material change within historic towns, especially when planning and cadastral documents are lacking. By integrating GAN-based colourisation of monochrome aerial photographs with automated roof segmentation, RoofChronoNet facilitates the extraction and diachronic mapping of various roof covering categories. The workflow aids in interpreting shifts in material regimes and phases of renovation rather than inferring building construction chronology from roof characteristics.

The application to Tirilye, Bursa, reveals that rooftop transformation is unevenly distributed across the settlement. Traditional red-tiled roofs remain concentrated within the historic centre, whereas white and dark grey roof coverings have become more prevalent in peripheral areas. This spatial variation renders material transitions perceptible at settlement scale and underscores the cumulative impact of incremental renovation practices on the historic urban fabric.

Methodologically, RoofChronoNet offers a reproducible framework for planning history focused on heritage, transforming visual archives into spatially explicit datasets that were previously unattainable through manual interpretation alone. The approach demonstrates how computational techniques can enhance traditional interpretive practices in urban morphology while remaining critically aware of the probabilistic and interpretive nature of colourised imagery. The approach nevertheless has important limitations. Colourised imagery represents a probabilistic reconstruction rather than a verified historical record, and segmentation performance is affected by class imbalance and image-quality constraints. Accordingly, computational outputs should be validated through field sur-

vey, archival documentation, or complementary evidence before informing regulatory or policy decisions.

The workflow can be adapted to other heritage contexts with similar morphological characteristics and, with appropriate retraining, to regions characterised by different roofing materials or architectural traditions. Future research may extend the approach through comparative multi-site studies and by integrating computational roofscape mapping with archival documents, cadastral records, and oral histories to strengthen historical interpretation.

Author Contributions: İ.C.I. developed the research design, managed the data collection process, and wrote the main sections of the manuscript. S.F.K. supervised the research, edited all parts of the manuscript, and revised the final draft. I.K. contributed to the development of the machine learning workflow, assisted in the analytical process, and participated in the writing of the manuscript. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement: The study generated derived data, including annotated roof samples, colourised imagery, segmentation outputs and model predictions. These materials are not publicly available due to ongoing doctoral research but can be provided by the corresponding author upon reasonable request.

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