Circinus: An AI-Based Technical Description Plotting

James Earl Cubillas[1], Rolyn Daguil[2]

[1] Virtual Learning Research Center, Caraga State University, Butuan City, Philippines – jdcubillas@carsu.edu.ph
[2] Department of Computer Science, College of Computing and Information Sciences, Caraga State University, Butuan City, Philippines – rcdaguil@carsu.edu.ph

Keywords: Land Survey Map, Convolutional Neural Networks, Automation, Computer Vision, Digitization, Opensource software.

Abstract

The digitization of maps poses a significant challenge for GIS operators and engineers, particularly in encoding bearings and distances into GIS software. This study, titled “Circinus: An AI-Based Technical Description Plotting,” represents a substantial advancement in the digitization process of land records. Leveraging artificial intelligence, this application enhances the efficiency of digitizing land survey maps, potentially surpassing the laborious manual input required for geographic information. By expediting the encoding process of scanned maps, the application enhances the accessibility and availability of digital land records. This advancement holds considerable benefits for effective land asset planning and improved financial operations, particularly benefiting prospective homebuyers and landowners. The tool offers streamlined encoding through its semi-automated features, facilitating ease of use. Additionally, its optimization features have the potential to significantly enhance the productivity of engineers and GIS operators involved in encoding scanned land survey maps.

1. Introduction

1.1 The Challenges in the Digitalization of Land Survey Records for Geospatial Data Archiving

The land property system in the Philippines, encompassing property titles, land records, and survey records, is characterized by exceptional complexity. These records predominantly exist in physical form, lacking digitalization or computerization. Given the country's archipelagic nature, the dispersal of land records presents a significant challenge. This absence of digitalization complicates the verification of land surveys and property titles, leading to a laborious, time-consuming, and costly procedure that is heavy to local legal counsels and agencies (Aban, 2016).

Recognizing the complexity of managing extensive land records, the Land Management Bureau of The Department of Environment and Natural Resources (DENR-LMB) has undertaken initiatives to address this issue. Spearheading the drive towards computerization, the Bureau aims to effectively manage cadastral maps, survey plans, land applications, patents, and titles. Implementing the Land Administration and Management System (LAMS) aligns with DENR’s Administrative Order 2010-18, dated June 23, 2010. LAMS is an information system tailored to streamline land record management, facilitating efficient land transactions and information dissemination to the public (LMB, 2010) (LMB, 2015). The system promises operational benefits such as enhanced efficiency, accountability, and accuracy in land-related transactions, improved accessibility to land records, and reduced costs for government, public, and private stakeholders.

DENR Central Visayas (DENR-7) exemplifies the successful adoption of LAMS, achieving significant milestones in land records digitization. Notably, in 2015, DENR-7 reported an accomplishment of 104 percent in digitizing land records, equivalent to 656,246 encoded land records and 926,580 scanned survey records, applications, patents, and titles. However, challenges persist in the digitization process, particularly regarding the accuracy and efficiency of data entry (LMB, 2016) (TheFreeman, 2016). While heads-up digitization has been employed to enhance accuracy, manual input of geographic information remains a resource-intensive task.

As organizations increasingly recognize the importance of digitization in modernizing processes, adopting advanced technologies such as GIS and web-based services becomes imperative. The transformation of GIS into a distributed system accessible via the web signifies a paradigm shift in how geographic information is utilized and shared. Despite the strides made in digitalizing land records, there is a pressing need to expedite the process, particularly in digitizing land survey maps (LMB, 2016). Streamlining backend processes and optimizing resource allocation are crucial steps towards enhancing the delivery of land-related services in the digital era.

1.2 Map Digitization

The process of map digitalization involves transforming geographical features from raw maps into digital formats, employing methods such as Manual Digitization, Heads-up Digitization, and Automated Map Digitization.

Manual Digitization involves encoding spatial features from raw maps using a digitization table equipped with a puck-like device, ensuring precision by electronically recording points and lines (Heywood et al., 2009) (GeospatialWorld, Digitization, 2009). Despite its effectiveness, manual digitization is labor-intensive and prone to positional errors, particularly without experienced operators. Heads-up Digitization digitizes digital images of maps displayed on a computer screen, requiring manual input in a GIS software environment due to the lack of geographic information (Heywood et al., 2009) (SurveyofIndia, 2002). Control points aid in accurately positioning features, with interactive tracing methods automating line outlining. Raster and Vector data are fundamental for conserving and utilizing images and graphics, with GIS and CAD software typically operating on raster-based or vector-based platforms (Wu, 2000) (Wu, 2010). Converting raster images to vector format requires careful consideration of factors such as image type, resolution, and preprocessing, with geo-referencing ensuring accurate spatial representation.

In essence, the digital transformation of maps opens new avenues for innovation and collaboration, empowering users to leverage geographic information for informed decision-making and resource management. As technology continues to evolve, the refinement of digital mapping techniques will play a pivotal role in shaping our understanding and interaction with the world around us.

1.3 Character and Object Recognition Techniques for Digitization Solutions

The automated conversion of raster to vector formats has spurred considerable research interest within the GIS and image processing communities. While existing commercial products have been effective in large-scale map digitizing and GIS data capture projects, there remains a need for further advancements and the development of novel algorithms and technologies.

1.3.1 Optical Character Recognition (OCR): Optical Character Recognition, or OCR, involves the electronic or mechanical conversion of images containing typed, handwritten, or printed text into machine-encoded text (Schantz, 1982). This process encompasses various applications, from scanning printed documents to extracting text from images or subtitles. OCR is vital in digitizing printed texts, enabling electronic editing, searching, and compact storage. Additionally, OCR finds application in machine processes such as cognitive computing, machine learning, and text mining. Despite its widespread use, OCR poses challenges in accurately recognizing text within maps and drawings due to diverse fonts, sizes, and orientations.

OCR Developed Applications	Usage
Computer Automated System and Method for Converting Source Documents Bearing Alphanumeric Text Relating to Survey Measurements (Solberg & LaPierre, 1995	The system converts an image file of a scanned source document bearing alphanumeric text relating to the lengths and directions of the boundary lines into a mathematically accurate vector computer drawing file. The digitized image file is imported into an existing CAD system with a COGO subroutine and an OCR operating within the CAD system.
Tesseract OpenSource OCR Engine	Tesseract (Vincent, 2006) is based on traditional computer vision algorithms. In the past few years, Deep Learning-based methods have surpassed traditional machine-learning techniques by a considerable margin in terms of accuracy in many areas of Computer Vision. Handwriting recognition is one of the prominent examples. Tesseract has implemented a Long short-term memory (LSTM) based recognition engine. LSTM is a Recurrent Neural Network (RNN) (Tesseractocr, 2020).
Google Cloud Vision API	Google developed a system capable of high-accuracy OCR in many languages. The Google Cloud Vision API is generally available (Google, 2018) (Walker et al., 2018). This OCR system is periodically tested on 232 languages in 30 distinct scripts, achieving state-of-the-art accuracy for most images ranging from scanned documents to casual photos.

Table 1. Recent Optical Character Recognition Applications.

1.3.2 Machine Learning-Based Character Recognition: Recent advancements in machine learning, particularly Convolutional Neural Networks (CNNs), have revolutionized object detection (Bhaidasna, 2023) and classification tasks. CNNs, inspired by the visual processing mechanisms of mammals, have demonstrated remarkable capabilities in various domains, including handwriting recognition. Meta-architectures such as Faster R-CNN (Uijlings, 2012), R-FCN (Dai et al., 2016), SSD (Liu, 2016), and YOLO (Redmoon, 2015) have significantly improved object detection accuracy and speed (Huang, 2017). These architectures leverage deep learning techniques to achieve state-of-the-art performance in real-time applications.

Machine learning-based character recognition techniques have found diverse applications, from banknote serial number recognition to document digitization (Lecun, 1998) (Choi et al., 2019) (Meier, 2010) (Shapiro, 2001); these methods enhance recognition accuracy and improve computational efficiency. Through techniques like knowledge distillation and Bayesian optimization, researchers continuously refine OCR systems to achieve higher performance and broader applicability across various domains.

1.4 Concept of the Study

The labor-intensive and protracted procedure of manually digitizing land survey records, particularly prevalent in institutions and practitioners in the Philippines, presents significant difficulties in efficient land administration. Current methodologies suffer from scalability, accuracy limitations, and substantial operational expenses. Acknowledging these challenges, a compelling imperative exists to pioneer an innovative application empowered by Artificial Intelligence (AI) to revolutionize data extraction from survey maps.

Thus, the researchers were driven to conceive Circinus, an AI-driven solution engineered to optimize the digitization process, thereby enhancing the efficiency, precision, and accessibility of land survey data by harnessing cutting-edge technologies such as machine learning and computer vision. Circinus endeavors to redefine the landscape of land administration.

The conceptual framework of this study is shown in Figure 1. The process commences with the utilization of a scanned map as the primary input data for the application. Users are guided to select a region corresponding to the table’s location within the application interface, manually inputting crucial information such as landowner details and tie line data from the survey plan. Upon completion, the region containing the technical description table undergoes image processing before undergoing automated processing for seamless data extraction.

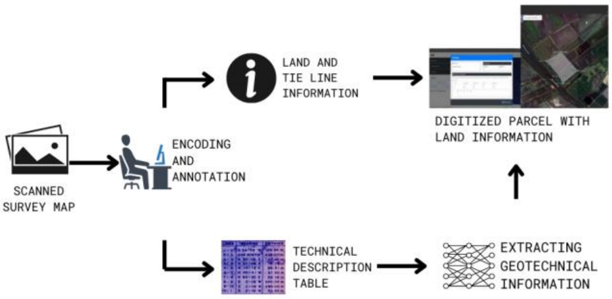

Figure 1. Conceptual Framework

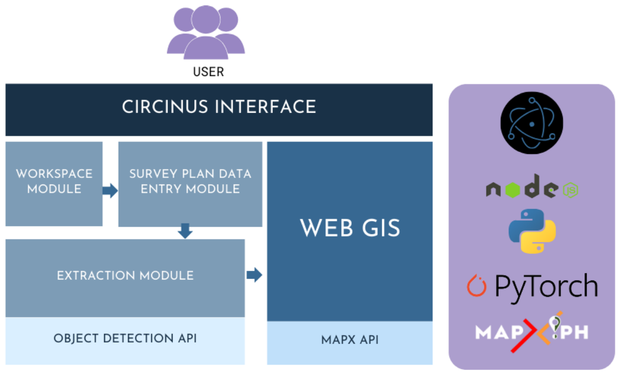

Figure 2. Circinus Architecture

2. Methodology

2.1 Materials

2.1.1 Software: Microsoft Windows 11 is the operating system, while back-end frameworks include Python, Pytorch, OpenCV, and Electron JS.

2.1.2 Hardware: The system unit features an Intel Core i5 9300H Coffee Lake Processor with 32GB RAM and an NVIDIA GeForce GTX-1050 GPU with 4GB VRAM.

2.1.3 Data: Land survey plans sourced from the Bureau of Fisheries and Aquatic Resources (BFAR) Fishpond License Agreement (FLA) Land Survey maps are used as training and testing images for developing transfer learning algorithms.

2.2 Application Development

2.2.1 Developing a Standalone Application: Circinus is crafted using Electron.js, an open-source framework maintained by GitHub. This framework facilitates the seamless creation of desktop graphical user interface (GUI) applications, leveraging the prowess of web technologies. Integrating the Chromium rendering engine with the Node.js runtime, Electron.js offers a robust foundation for building versatile applications.

The architecture of Circinus, as depicted in Figure 2, adheres to a stack approach, strategically modularizing functionalities into three core components: the workspace module, survey plan data entry module, and extraction module. The workspace module is the cornerstone for profiling the extraction instance, meticulously organizing all temporary files, and extracting data output within the designated working folder. The process seamlessly transitions to the Survey Plan Data Entry Module, an intuitive annotation tool. Within this module, users can precisely select the location of the Technical Description Table and manually input pertinent land information details along with tie line information. Upon completion of annotation and encoding, the annotated Technical Description Table seamlessly undergoes data extraction within the Extraction Module. Leveraging the Object Detection API, geotechnical data is meticulously extracted, ensuring accuracy and reliability. Subsequently, the digitized data is seamlessly displayed within the Web-GIS interface, harnessing the capabilities of the MapX API for visualization and analysis.

2.2.2 Classification Machine Learning System: The Classification Machine Learning System employed in this study utilized three (3) Convolutional Neural Network (CNN) models, specifically YOLOv5s, to discern and classify crucial elements such as bearing, distance, number blocks, and numeric values within the Technical Description (TD) table. This approach was adopted to mitigate the potential for misclassification from the many classes in the image.

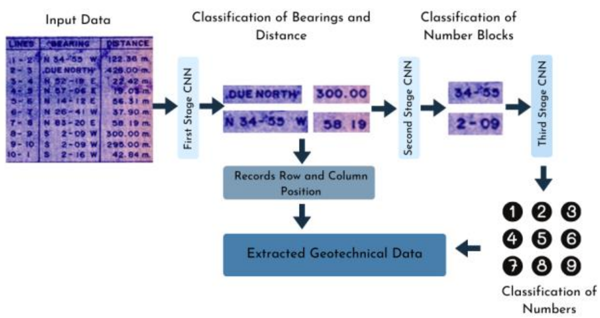

Figure 3. Classification Machine Learning System of the Object Detection API

Figure 3 provides an illustrative depiction of the stages involved in object detection and classification. Initially, the first CNN model identifies Regions of Interest (ROI) about direction and distance within the Technical Description table, automating the cropping process for these elements. The program records these cropped images' positional coordinates (x, y), facilitating the accurate display of extracted data in the final stage. Subsequently, the second CNN model classifies the number blocks within the ROI, which is then utilized in the subsequent stage for numeric values classification. Following classification, the program utilizes the recorded x and y coordinates of the images to precisely position each extracted numeric and textual data within the rows and columns of the Bearing and Distance table, mirroring the layout of the Technical Description table.

Upon completion of the extracted process, the data is saved in lightweight data interchange formats such as Comma-Separated Values (CSV) and JavaScript Object Notation (JSON), ensuring compatibility and ease of access for further analysis and utilization.

3. Results and Discussions

3.1 Circincus App Development

3.1.1 Circincus User Interface Overview: The Circinus Landing Page is the gateway to the application's various sub-pages and features. Figure 4 illustrates the app's menu interface, encompassing links to subsequent modules.

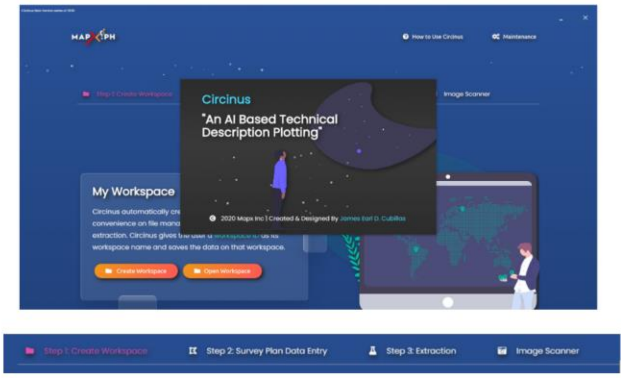

Figure 4: Circinus User Interface.

3.1.2 Modules Description: The Circinus application is structured into modules, each designed to fulfill distinct functionalities such as Workspace Management, Survey Plan Data Entry, and Extraction Modules.

Workspace Module: Within this module, as shown in Figure 5, users are prompted to establish a workspace for organizing all data selection and extraction files. Upon initiating the "Create Workspace" command, a dedicated folder is generated within the Circinus directory, adopting the workspace ID as its folder name.

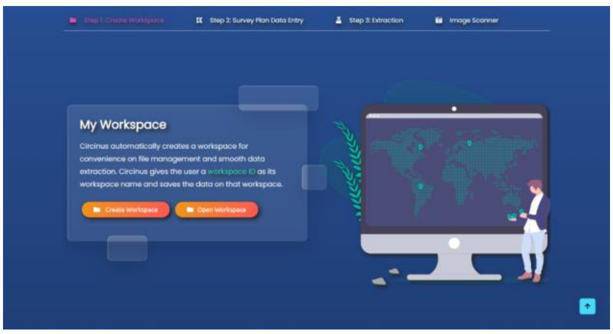

Figure 5: Workspace Module.

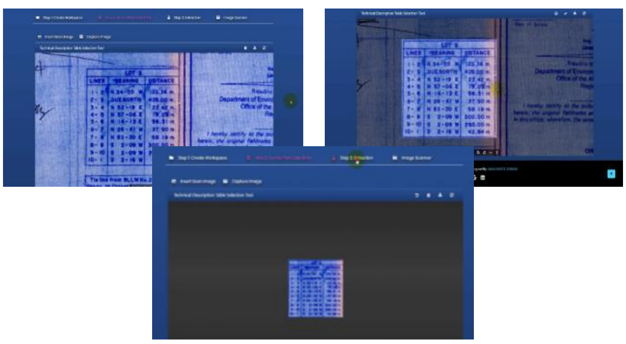

Figure 6: Selecting the Technical Description Table using Imaging tools.

Survey Plan Data Entry Module: This module facilitates data input into the Circinus application, as shown in Figure 6. It features a Technical Description Table Selection interface, enabling users to assign the Technical Description Table via the application's imaging tools.

Extraction Module: The Extraction Module functions as the data extraction mechanism within the Circinus application. As shown in Figure 7, the cropped image undergoes a data extraction process employing a three-staged convolutional neural network. Upon completion, the application presents the successfully extracted details from the Technical Description table and provides a notification indicating the time elapsed during the extraction process. After data extraction, users must input the lot's reference points to ensure accurate visualization in the WebGIS powered by the MapX API. Notably, as the Philippine Reference System 1992 (PRS92) coordinate system is prevalent in the Philippines, coordinates must be converted to WGS84:EPSG4326, aligning with the coordinate system utilized by WebGIS platforms.

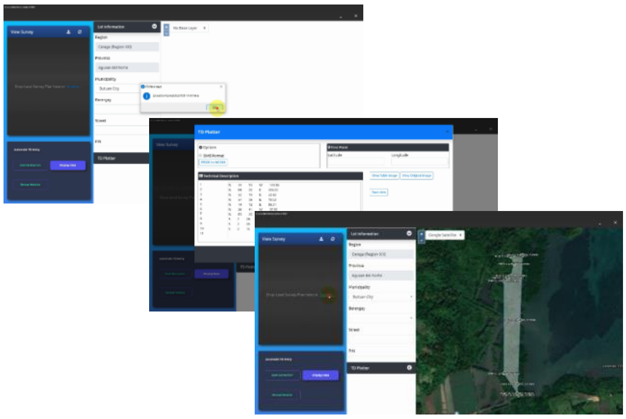

Figure 7: Data Extraction to Digitized Parcel Process.

3.2 Performance and Evaluation

3.2.1 Evaluation of CNN Models: A thorough series of tests and evaluations have been conducted on the three CNN models employed in this study. The initial CNN model demonstrated exceptional performance in classifying direction and distance attributes.

Figure 8 showcases an example of the classification output achieved by the First CNN Stage, while Figure 9 presents the confusion matrix detailing the model's performance metrics.

The second stage specializes in classifying Bearing number blocks and Distances within the Technical Description (TD) table. Notably, the similarity in structure and features between distance values and bearing numbers facilitates efficient examination within this context.

Figure 10 illustrates the classification output for Bearing and Distance utilizing the Second CNN Stage, while Figure 11 presents the multi-class metric evaluation for this model.

The third stage is dedicated to the classification of numerical values. Within the output list, each prefix corresponds to the x-coordinate of the bounding box encapsulating the classified number. This systematic approach ensures precise preservation of the order of classified numbers as depicted in the original image.

Figure 13 depicts the object detection procedure for Numeric Values employing the Third CNN stage and the confusion matrix outlining the model's performance metrics in Figure 14.

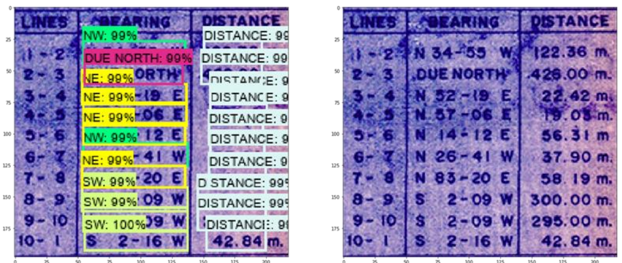

Figure 8. Example Classification Output of First CNN Stage

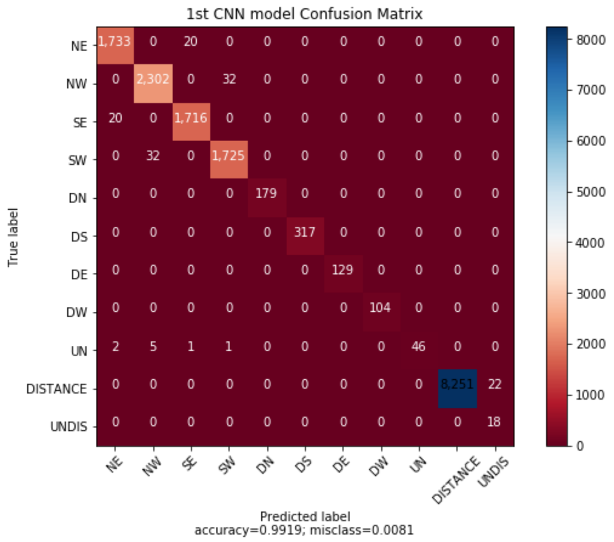

Figure 9. Confusion Matrix of the First CNN Stage

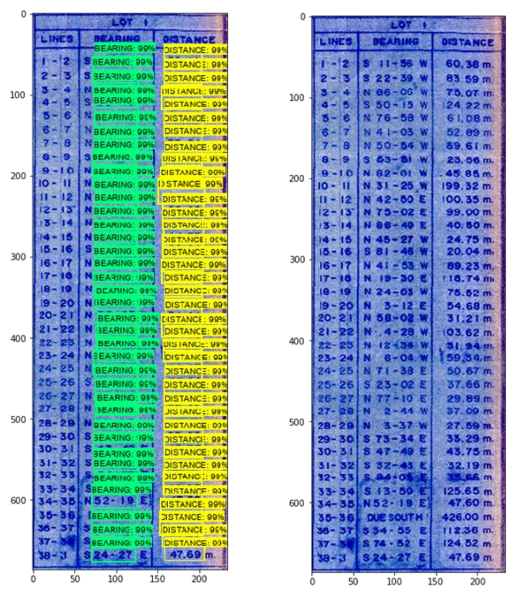

Figure 10. Classification Output of Bearing(Number Block) and Distance (Number Block) of the Second CNN Stage

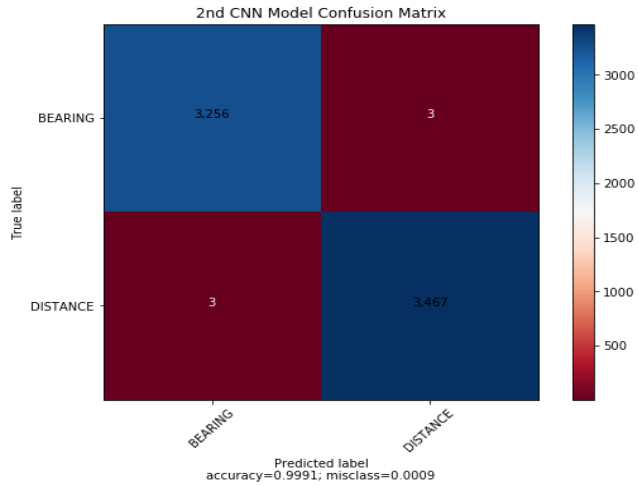

Figure 11. Confusion Matrix of the Second CNN Stage

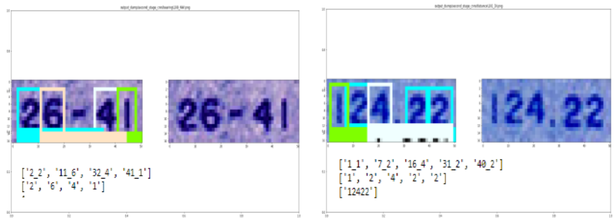

Figure 12. Classification of Numeric Values using the Third CNN Stage

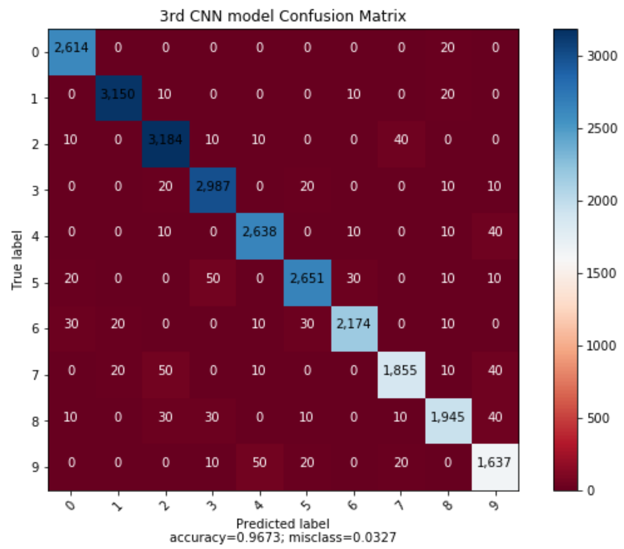

Figure 13. Confusion Matrix of the Third CNN Stage

4. Summary

The digitization of Land Survey Plans poses a significant challenge within Geographic Information Systems (GIS). To address this complexity, the researcher has meticulously crafted the Circinus to streamline the digitization process, particularly in the context of heads-up digitization. Leveraging its precision, the Circinus app surpasses traditional manual encoding methods, yielding intricately encoded Land Survey maps with unparalleled accuracy. By expediting the encoding process of scanned maps, the app enhances the accessibility and availability of digital survey plans, offering substantial benefits to its users.

Employing Electron JS as the software framework, the researcher has engineered Circinus as a desktop application utilizing web technologies such as HTML, CSS, and JavaScript. Electron JS is a superior alternative to native desktop applications due to its inherent resemblance to Web Apps. While Web Apps are limited to downloading files to the computer's file system, Electron Apps can access and manipulate the system, facilitating seamless data read and write operations. Furthermore, Electron JS facilitates seamless communication with Python, serving as the computational backbone of the application.

In the domain of extraction methodologies, Convolutional Neural Networks (CNN), particularly the Faster RCNN Inceptionv2 model, demonstrate superior performance compared to alternative techniques such as Optical Character Recognition (OCR). Through rigorous experimentation, employing three distinct CNN models for various extraction processes underscores their effectiveness in retrieving GIS information. The Circinus application's encoding efficiency and performance were meticulously evaluated using the BFAR survey maps validation dataset, generating highly accurate GIS data extractions.

5. Conclusions

Based on the results and findings explained in this study, the following conclusions can be drawn:

1. The successful classification of land survey plans within the Circinus application was achieved through the adept utilization of convolutional neural networks, specifically leveraging the YoloV5s architecture as a robust classifier.

2. Implementing three distinct CNN models tailored for various classification tasks demonstrated its efficacy in extracting technical data with precision and accuracy.

The study's outcomes underscore the effectiveness of the proposed methodology across the stages of the extraction process, as evidenced by the validation dataset experiments. The Circinus application emerges as a valuable tool for the extraction of technical data from land survey plans, thus affirming the attainment of the study's objectives.

6. Contributions

Circinus leverages open-source technologies, enabling web-based collaboration among GIS professionals. This collaborative approach enhances the accuracy and efficiency of map digitization and promotes knowledge sharing and collective problem-solving within the GIS community. Using open-source tools ensures the technology is accessible to a wider audience, facilitating educational opportunities and outreach efforts in the geospatial field.

References

Aban, J. Philippines: Enhancing Community Resource Mapping Through GIS., 2016. Asian Development Bank Technical Assistance Consultant’s Report.

Bhaidasna, H. Bhaidasna, Z., 2023. Object Detection Using Machine Learning: A comprehensive Review, International Journal of Scientific Research in Computer Science, Engineering and Information Technology, Volume 9, Issue 3, 248-255.

Choi et al., 2019. Machine Learning-Based Character Recognition Applications: Machine Learning-Based Fast Banknote Serial Number Recognition Using Knowledge Distillation and Bayesian Optimization. Sensors, No. 19, 4218

Chiang, Y., Knoblock, C., 2014. Recognizing text in raster maps. Geoinformatica, Springer.

CivilSeek., 2020. Chain Surveying: Its Procedure, Instruments, and Principles. https://civilseek.com/chain-surveying/.

Dai, J., Li, Y., He, K., & Sun, J., 2016. R-FCN: Object Detection Via Region-based Fully Convolutional Network. arXiv, 1-11.

Duda, R., & Hart, P., 1972. Use of the Hough Transformation to Detect Lines and Curves in Pictures. Commun. ACM, 11-15.

GeospatialWorld.(2009).Digitization. https://www.geospatialworld.net/article/digitisation/.

Girshick, R., 2015. Fast R-CNN. arXiv.

Girshick, R., Donahue, J., Darell, T., & Malik, J., 2014. Rich Feature Hierarchies for Accurate Object Detection and Semantic Segmentation. arXiv.

Google, (2018). Google Cloud Vision AI. https://cloud.google.com/vision.

Heywood, I., Cornelius, S., & Carver, S., 2009. An Introduction to Geographical Information Systems, Third Edition. Prentice Hall.

Huang, J., Rathod, V., Sun, C., Zhu, M., Korattikara, A., Fathi, A., Murphy, K., 2017. Speed/Accuracy Trade-offs for Modern Convolutional Object Detectors. arXiv:1611.10012v3 [cs.CV], pp. 1-21.

LeCun, Y., Bottou, L., Bengio, Y., & Haffner, P., 1998. Gradient-Based Learning Applied to Document Recognition. PROC. OF THE IEEE, 1-46.

Liu, W., Anguelov, D., Erhan, D., Szegedy, C., Reed, S., Fu, Y., & Berg, A., 2016. SSD: Single Shot MultiBox Detector. arXiv, 1-11.

LMB., 2010. About The Land Administration and Management System (LAMS). https://lmb.gov.ph/index.php/e-library/land-administration-and-management-system/about-lams.

LMB., 2015. The Land Administration and Management System (LAMS). https://lmb.gov.ph/index.php/86-programs-and-projects/i-land-administration-and-management-system-lams/9-lams.

LMB., 2016. LMB land records computerization project gears up. https://lmb.gov.ph/index.php/about-us-1/regional-director/8-home-article/79-fast-track-land-titling-for-public-schools-orders-paje.

Meier, U., Gambardella, L. M., & Schmidhuber, J., 2010. Deep Big Simple Neural Nets Excel on Handwritten Digit Recognition. Neural and Evolutionary Computing, Volume 33, Number 12, 1-14.

Redmoon, J. et.al, 2015. You Only Look Once: Unified, Real-Time Object Detection, arXiv:1506.02640.

Schantz, H.,1982. The History of OCR, Optical Character Recognition. Manchester Center, Vt. Recognition Technologies Users Association.

Shapiro, L., & Stockman, G., 2001. Computer Vision". New Jersey: Prentice-Hall, ISBN 0-13-030796-3.

Solberg, S., & LaPierre, L., 1995. Computer Automated System and Method for Converting Source Documents Bearing Alphanumeric Text Relating to Survey Measurements. United States Patent, Patent Number: 5,761,328.

SurveyofIndia., 2002. Data Model for Digital Cartographic Vector Database Creation on Microstation Based Systems. Dehradun: Modern Cartographic Centre, Survey of India.

Tesseract-OCR., 2020. Tesseractv4. https://github.com/tesseract-ocr/tessdoc/blob/master/4.0-with-LSTM.md.

TheFreeman., 2016. Digitization strengthens the LAMS program – DENR. https://www.philstar.com/the-freeman/cebu-news/2016/01/03/1539109/digitization-strengthens-lams-program-denr.

Uijlings, J., 2012. Selective Search for Object Recognition. IJCV.

Vincent, L., 2006. Announcing Tesseract OCR.

Walker, J., Fujii, Y., & Popat, A., 2018. A Web-Based OCR Service for Documents. 13th IAPR International Workshop on Document Analysis Systems (pp. 21-22). Vien-na, Austria: IAPR.

Wu, Y., 2000. Raster, Vector, and Automated Raster-to-Vector Conversion", in "Moving Theory into Practice: Digital Imaging for Libraries and Archives." RLG, Cornell Univ. Library.

Wu, Y., 2010. R2V: Automated Map Digitising. https://www.geospatialworld.net/article/r2v-automated-map-digitising/.