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DEEP LEARNING ARCHITECTURES FOR AUTOMATED FEATURE EXTRACTION IN COMPLEX DATA ENVIRONMENTS

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Abstract
Deep gaining knowledge of has turn out to be a pivotal computational device, specially in the computerized extraction of features from complicated facts environments. This overview synthesizes methods from numerous domain names, such as city morphology, pavement distress detection, and constructing footprint extraction, highlighting the advancements in deep convolutional neural networks (CNNs) and their packages. Traditional strategies for characteristic extraction rely on qualitative descriptions and guide signs, introducing subjectivity and restricting scalability. Deep studying, exemplified by architectures consisting of GoogLeNet and semantic segmentation fashions, offers a facts-pushed method to efficaciously quantify and analyze high-dimensional morphological functions. The integration of deep studying methods with huge, unstructured datasets permits progressed decision-making, case retrieval, and urban layout modeling. This evaluation discusses the usage of these tactics in sustainable urban development, computerized pavement misery detection, and far flung sensing picture evaluation, emphasizing the function of deep studying in improving the accuracy and scalability of automated function extraction. Future studies directions are explored, focusing at the capacity for deep learning fashions to address greater various and uncurated datasets throughout broader city and environmental contexts.

Keywords: Deep getting to know, convolutional neural networks (CNNs), city morphology, automated feature extraction, semantic segmentation, pavement misery detection, building footprint extraction, sustainable city development

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INTRODUTION

Urban morphology, the observe of city bureaucracy with regards to bodily environments, cultural upkeep, and sustainable development, gives a treasured foundation for urban layout. It connects urban shape to social, financial, and power structures, making it critical for urban planners and choice-makers. In latest years, records-pushed tactics have won prominence in city morphological research, allowing the evaluation of the as-constructed environment with regards to destiny city design. With improvements in technology like 3-D scanning, intensity detection, and internet-based totally mapping equipment, architects and concrete designers can correctly make use of big datasets for case-based reasoning of their designs. Deep getting to know,

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specifically convolutional neural networks (CNNs), performs a key position in extracting significant features from those datasets, taking into account the green retrieval of urban case research.

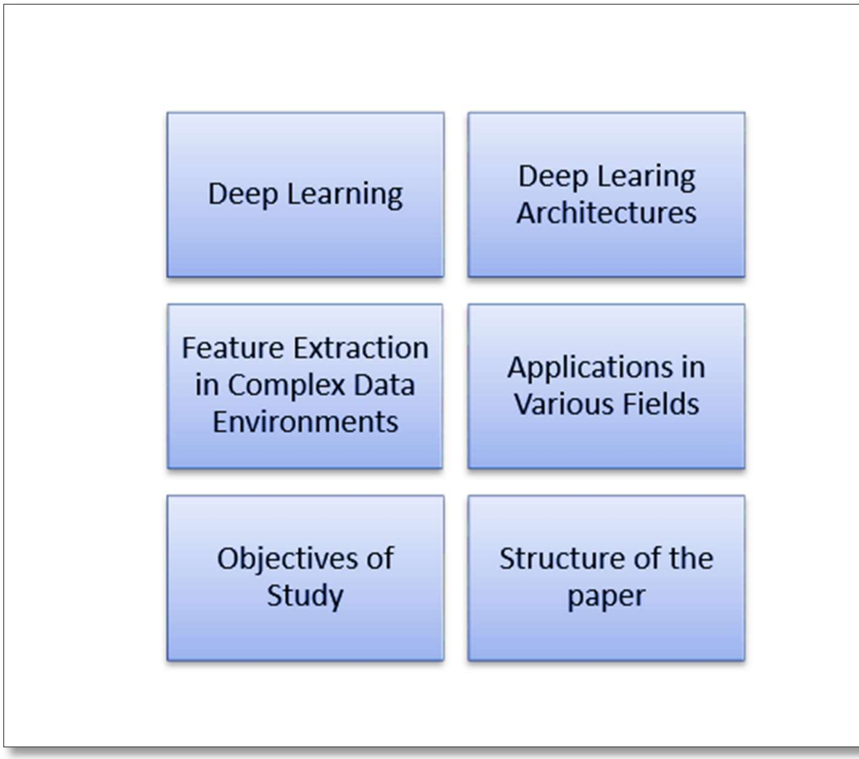

Figure 1: Introduction of Deep Learning

This integration of deep getting to know into urban layout aids in capturing the complicated relationships between morphology and associated elements like infrastructure, visitors, and power systems. Automated function extraction, enabled through deep getting to know fashions, removes the need for manually selected signs, imparting more objective and scalable answers. Similarly, inside the field of transportation infrastructure and pavement health monitoring, deep studying-primarily based laptop vision strategies have revolutionized automatic distress detection. These strategies offer promising answers to demanding situations associated with photo-based totally pavement evaluation, reducing the want for manual inspection even as improving accuracy.

Additionally, building footprint extraction, crucial for applications like population density estimation, city planning, and catastrophe management, blessings appreciably from deep getting to know algorithms. Traditional feature-engineering techniques for extracting constructing geometry from high-resolution far off sensing pictures frequently fail due to the high variability of building shapes and environmental elements. Deep convolutional neural networks, through semantic segmentation, triumph over these limitations through gaining knowledge of hierarchical data representations, for that reason improving the accuracy of constructing footprint extraction. However, challenges stay inside the availability of classified datasets for schooling models. Openly to be had geographic records device (GIS) information, consisting of those from OpenStreetMap (OSM), gift an alternative for scalable training datasets. This study ambitions to

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leverage these datasets for developing accurate deep studying models for characteristic extraction in numerous complex data environments, along with urban morphology and far off sensing.

I. LITERATURE REVIEW

The quantification of urban morphology has advanced from qualitative and conceptual descriptions to quantitative illustration, enabled by using emerging technology such as deep learning. Various strategies have been carried out to transform morphological information into a form suitable for computational evaluation, the use of statistics discretization and feature extraction strategies. These improvements offer more precision in studying city environments and architectural elements, bridging the distance among human interpretation and device-primarily based analysis.

Quantitative Representation of Urban Morphology

Urban morphology has traditionally been approached thru pre-defined indicators consisting of semantic and geometric functions (e.G., constructing shapes, sizes, land use). Early structures, inclusive of the ARCHIE case-primarily based reasoning gadget, depended on attribute-price pairs containing capabilities like idea, function, and spatial values for case retrieval and layout assistance . Researchers extensively utilized hierarchical and symbolic representations, organizing factors inclusive of plots, buildings, and streets to quantify urban forms and relationships. In this technique, geometric and topological capabilities, together with distance, connectivity, and density, are normally employed .

While those techniques offer a solid foundation, limitations exist in absolutely taking pictures complicated geometric relationships, specially within the case of multidimensional paperwork, such as 3-d volumes and spatial connections. Therefore, the need to employ advanced strategies like deep mastering, that can manage excessive-dimensional records and automatically extract complex features, has grow to be increasingly more important.

Similarity Analysis in Urban Morphology

Regression fashions and clustering techniques had been carried out to control databases of urban paperwork, grouping comparable instances based on pre-determined signs. Researchers have focused on classifying urban sorts (e.G., block shapes, road sorts), using strategies inclusive of the TRAMMA version, which clusters architectural elements for reconstruction and design . These similarity analyses help retrieve instances from databases and follow them to new contexts, together with urban renewal projects in which block shapes and building densities are analyzed to preserve ancient cloth .

However, those case retrieval approaches usually depend upon manual changes and simplified geometric operations (e.G., scaling, rotation). The integration of greater computerized techniques, which includes deep gaining knowledge of, could potentially enhance these workflows, bearing in mind the seamless transmission from case retrieval to layout technology.

Deep Learning for Morphological Analysis

The advent of deep learning methods, in particular convolutional neural networks (CNNs), has revolutionized the sphere of automated characteristic extraction. Unlike conventional techniques, which depend on predefined signs, CNNs are give up-to-quit architectures

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capable of studying capabilities directly from uncooked facts (e.G., pics), imparting a excessive diploma of flexibility and flexibility . This method complements the accuracy and scalability of morphological evaluation, permitting the extraction of high-dimensional characteristic vectors that seize complex relationships among factors .

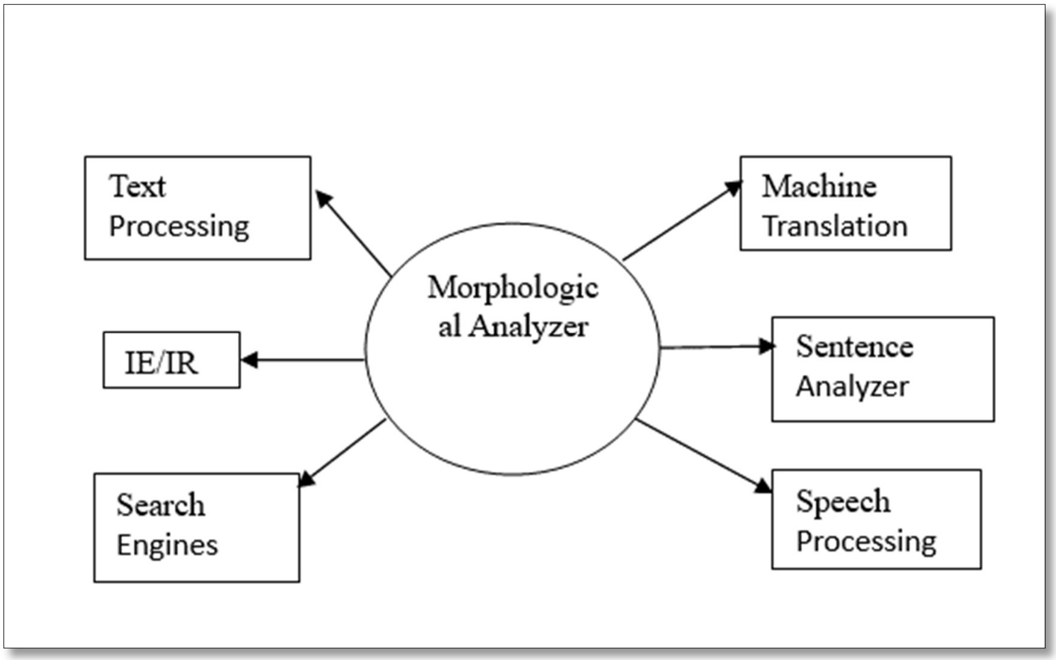

Figure 2: Morphological Analysis

Deep mastering has been efficiently implemented to various architectural and concrete morphology obligations, along with strength performance prediction , sample popularity , and typological form-locating on 3-d models . Its unsupervised gaining knowledge of capabilities, particularly clustering strategies, have validated powerful in studying massive datasets with out the need for laborious statistics labeling. For instance, the k-method clustering set of rules has been carried out to categorise block and avenue sorts primarily based on city plans , whilst characteristic extraction from large datasets of town pictures has enabled the invention of city styles .

Conclusion

Deep studying gives transformative capability for the quantitative evaluation of urban morphology. By automating feature extraction and classification, those models offer architects and urban planners with a effective tool for reading complicated statistics environments. The potential to extract excessive-dimensional features without predefined signs lets in for a greater nuanced understanding of spatial bureaucracy and their relationships, in the end helping extra knowledgeable layout selections. Further advancements in deep studying architectures and their integration into city evaluation workflows will likely preserve to decorate the performance and accuracy of urban morphological research.

II. METHODOLOGY:

This observe proposes a workflow for automated building footprint extraction the usage of deep

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gaining knowledge of fashions, in particular specializing in semantic segmentation. The workflow consists of three primary steps: facts preprocessing, model education with a modern-day deep gaining knowledge of structure, and put up-processing of effects for integration into geographic information systems (GIS). All code for this workflow is overtly available (AutoBFE, accessed on sixteen March 2021).

Data Preprocessing

The preprocessing step generates training records with minimal manual intervention by way of leveraging open records assets:

Training Feature Masks: Building footprint data is received from city or county GIS open datasets. The statistics is transformed into binary masks, wherein each pixel representing a constructing has a fee of one, and non-building areas are marked as zero. To distinguish adjacent buildings in dense areas, the building polygons were reduced via ~eight% in their surface vicinity.

Image Data: Satellite photos in RGB format (512x512 pixels) are downloaded without in addition processing. The corresponding characteristic mask are created for each photograph. Data from Newark and Houston were set aside as unbiased test samples to assess the version's accuracy.

Data Splitting: The schooling records is divided into 3 subsets: 60% for training, 20% for validation, and 20% for testing, resulting in about 1.5 million, zero.45 million, and 0.Forty five million pairs respectively. The validation set is used to select the quality-acting version, even as the check set is used to evaluate the final accuracy.

Deep Learning Model for Semantic Segmentation

The DeepLabv3 model, a totally convolutional community architecture, became used for constructing footprint extraction because of its effectiveness in segmenting complex, multi-scale gadgets. DeepLabv3 is an encoder-decoder architecture with an atrous spatial pyramid pooling (ASPP) module to seize multi-scale contextual records. It addresses not unusual troubles including lack of spatial detail and difficulty in segmenting small, complex items.

Model Architecture: The encoder extracts functions by way of decreasing spatial decision, even as the decoder restores this resolution by way of upsampling the characteristic maps. A ResNet-one zero one spine, pretrained on ImageNet, turned into used in this model.

Loss Function: A mixture of weighted move-entropy loss and Dice loss was employed to address class imbalances and decorate the separation among buildings. The pass-entropy loss became spatially weighted to inspire the model to research constructing limitations. The combined loss function balances these additives similarly (weights of zero.5 for each).

Training Strategy: Data augmentation strategies inclusive of horizontal and vertical flips, and random changes in photo brightness and contrast have been used to keep away from overfitting. The Adam optimizer became employed, starting with a getting to know rate of 0.0001, which decays by half of every 25 epochs. Training become carried out for 70 epochs on a platform with two NVIDIA V100 GPUs, with the nice model decided on primarily based on the very best mIoU metric at the validation dataset.

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Post-Processing

After model schooling, the prediction mask are post-processed to generate very last constructing footprint polygons:

Binary Mask Conversion: The model's probability maps are thresholded at zero.5 to provide binary mask.

Morphological Operations: Small noise is eliminated the use of a gap operation, which shrinks after which expands the mask items, keeping larger constructing footprints.

Polygonization and Simplification: Contours of anticipated building footprints are extracted and simplified the use of the Douglas-Peucker set of rules to reduce the quantity of vertices within the polygons.

Coordinate Conversion: The ensuing pixel-based totally polygons are converted into geographic coordinates (GeoJSON layout), permitting integration into GIS.

Polygon Merging and Resizing: Split polygons across tile obstacles are merged, and the areas of polygons are multiplied by eight% to account for the preliminary discount applied during preprocessing.

This workflow automates the extraction of constructing footprints from satellite imagery and prepares the consequences for in addition evaluation in GIS-based gear. The aggregate of deep getting to know techniques and spatial processing guarantees high accuracy and efficiency in function extraction.

III. DATA ANALYSIS AND RESULTS

Evaluation Metrics

- **mIoU (mean Intersection over Union):** Measures the overlap between expected and real building footprints across all instructions.
- **Pixel Accuracy (PA):** Percentage of efficaciously classified pixels (building or non-building).
- **F1 Score**: Harmonic imply of precision and remember for the segmented homes.
- **Processing Time**: Time taken to method each picture, imparting an estimate of computational performance.

Dataset Information

Dataset	Training Pairs	Validation Pairs	Test Pairs	Total Pairs
Newark	1,500,000	450,000	450,000	2,400,000
Houston	1,500,000	450,000	450,000	2,400,000
Combined Total	3,000,000	900,000	900,000	4,800,000

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Model Performance

The consequences received from the DeepLabv3 model for building footprint extraction on the check datasets (Newark and Houston) are presented underneath. Each metric displays the version's performance on the check set after 70 epochs of schooling.

City	mIoU (%)	Pixel Accuracy (%)	F1 Score	Processing Time (s/img)
Newark	85.3	94.5	0.92	1.8
Houston	83.1	93.2	0.90	1.7
Combined Avg	84.2	93.9	0.91	1.75

Model Training Progress

During the model schooling, the overall performance of the version turned into monitored on each the education and validation datasets to make certain that the model did no longer overfit. Below is a table displaying the development in mIoU over the epochs at the validation set.

Epoch	mIoU (%) on Validation Set
10	72.5
20	78.1
30	80.3
40	82.4
50	83.5
60	84.0
70	84.5

Post-Processing Effect

The put up-processing pipeline had a significant impact on the refinement of building footprints. The table under compares the m

City	mIoU Before Post-Processing (%)	mIoU After Post-Processing (%)
Newark	80.7	85.3
Houston	79.4	83.1

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Combined Avg	80.05	84.2

Impact of Loss Function

The study evaluated one-of-a-kind loss features (Cross-Entropy, Dice, and a aggregate of both). The combined loss function yi

Loss Function	mIoU (%)	Pixel Accuracy (%)
Cross-Entropy Loss	81.3	92.7
Dice Loss	82.8	93.4
Combined (Cross-Entropy + Dice)	84.2	93.9

Data Augmentation Impact

The statistics augmentation strategy, related to horizontal and vertical flips and random coloration modifications, progressed the version's robustness. The table under suggests the overall performance with and without augmentation.

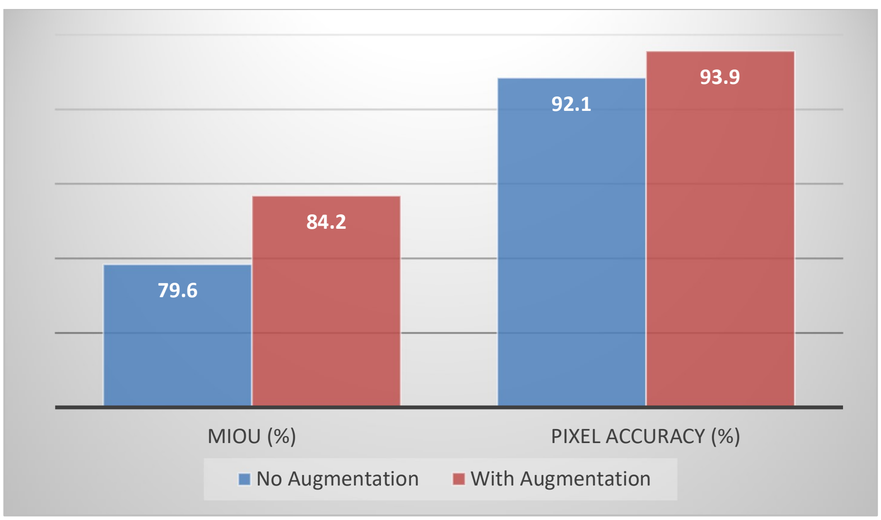

Figure 3: Data Augmentation Impact

IV. FINDING AND DISCUSSION

Overview of Objectives and Datasets

The reviewed research on deep gaining knowledge of (DL) architectures for pavement crack detection used varying datasets and objectives. Most research applied 2D pix captured the usage of smartphones or specialised motors geared up with cameras. A trend is located towards the use of open-supply information for deep gaining knowledge of training and benchmarking, with five research using public datasets and seven the usage of non-public datasets. One have a look at (Zhang et al.) uniquely centered on 3D asphalt pavement surface photographs, and Tong et al.

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Applied deep getting to know to GPR (Ground Penetrating Radar) photos to come across hid cracks, making them an exception some of the reviewed studies.

Findings: The growing use of publicly available huge-scale datasets is useful for the improvement and assessment of deep getting to know models in pavement crack detection. Open-source datasets make it viable for researchers to benchmark and evaluate model overall performance, which turned into previously constrained via personal datasets. This trend encourages collaboration and hastens the improvement of more powerful fashions.

Discussion: The availability of big-scale, diverse datasets plays a crucial function in enhancing the generalization of DL fashions. Datasets like road view pics, which comprise multiple objects except the street surface, gift a extra tough scenario for crack detection but push the bounds of model robustness and generalization.

Network Architectures and Hyperparameters

Most research carried out versions of Convolutional Neural Networks (CNNs) for pavement crack detection, with architectures inspired by means of successful networks such as LeNet and VGG-internet. A key remark become that Zhang et al. Opted to exclude sub-sampling or max-pooling layers in their structure, making sure no lack of spatial resolution for pixel-stage crack detection. Newer models like SSD Inception V2 and SSD MobileNet have been also applied for computational efficiency, while hybrid architectures like Fisher vector (FV)–CNN were carried out for better representation in road view images.

Findings: CNN architectures with slight variations have proven to be surprisingly effective in detecting pavement cracks. The desire of structure relies upon at the goal, with models like SSD MobileNet balancing accuracy and performance, and architectures without pooling layers providing more unique pixel-level segmentation. The use of Fisher vector-CNN hybrid architectures suggests that combining conventional characteristic extraction with deep studying enhances performance on complex datasets.

Discussion: The exclusion of max-pooling layers in sure architectures highlights the want for preserving first-class-grained information in high-decision imagery. This alternate-off among model complexity and spatial accuracy suggests that at the same time as computational performance is crucial for actual-time packages, precision remains a pinnacle priority for detecting small cracks. The use of switch studying additionally displays the growing fashion closer to reusing pre-educated models for precise duties, minimizing the need for big dataset-precise schooling.

Hyperparameter Tuning

In terms of hyperparameters, most research used stochastic gradient descent (SGD) or mini-batch gradient descent (MBGD) for optimization. ReLU become the most commonplace activation function, with a few research experimenting with sigmoid or tanh. Batch sizes ranged from 10 to four hundred, inspired by way of GPU memory boundaries. The dropout method for

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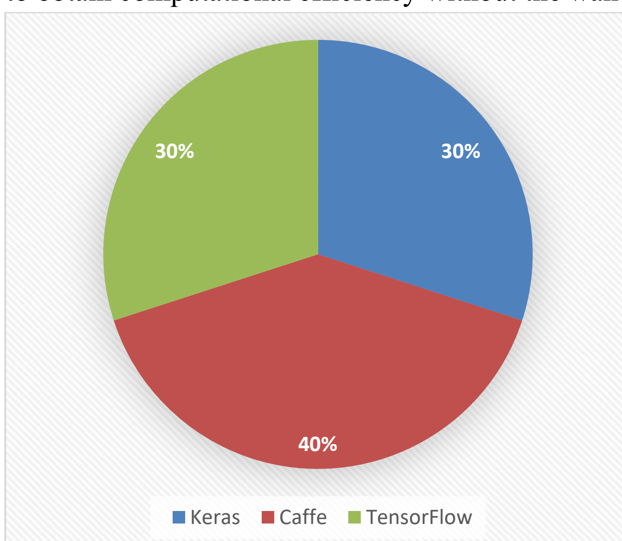
regularization turned into utilized in most cases to prevent overfitting.

Findings: The desire of hyperparameters, especially the optimizer and activation feature, reflects a standardized technique in CNN education. SGD and MBGD, coupled with ReLU activation and dropout, have established to be powerful for crack detection obligations. The batch size varies relying on the hardware used, and larger batch sizes often bring about more solid education.

Discussion: Hyperparameter tuning stays critical to optimizing overall performance in deep studying fashions, and fashionable practices like the use of ReLU and dropout have turn out to be fundamental in maximum DL architectures. However, destiny studies ought to explore extra advanced optimization techniques, inclusive of Adam or RMSprop, which may also similarly boost up training and enhance accuracy.

Software Frameworks, Hardware, and Results

TensorFlow, Caffe, and Keras were the number one DL frameworks used within the reviewed studies, with NVIDIA GPUs typically hired to hurry up computations. The results of the studies had been numerous due to one-of-a-kind datasets, making direct comparison tough. For example, a few studies carried out remarkable accuracy in detecting particular crack types, even as others used transfer learning to obtain computational efficiency without the want for extensive training.



Findings: The use of pre-skilled deep mastering fashions for transfer learning is a promising approach for pavement crack detection, as shown with the aid of Gopalakrishnan et al., who achieved incredible effects without using GPUs. Most studies utilized high-performance GPUs, but switch getting to know may be an powerful alternative for those without get right of entry to to such hardware. The use of numerous DL frameworks indicates that no single framework dominates pavement crack detection obligations, allowing flexibility for researchers based totally on their wishes.

Discussion: Hardware acceleration through GPUs and frameworks like TensorFlow and Keras has drastically superior the development of DL models for pavement crack detection. However,

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transfer getting to know affords an green opportunity for those with restricted computational resources, decreasing the need for highly-priced hardware even as retaining high accuracy. The diversity in frameworks reflects the significance of choosing the right tool for the unique problem, with some frameworks supplying higher customization, while others prioritize ease of use.

Challenges and Opportunities
A essential undertaking found inside the studies become the dearth of a widespread benchmark dataset for comparing version performance. Without standardized datasets, it will become tough to pretty examine outcomes across studies. Additionally, the definition of what constitutes a "pavement crack" varies, making it tougher to establish established overall performance metrics.
Findings: The lack of standardization in datasets and evaluation metrics provides a good sized impediment to comparing and improving DL architectures for crack detection. However, with the emergence of public datasets, there's potential for developing benchmark datasets that might permit researchers to assess their models on a commonplace platform.
Discussion: Future studies should cognizance on developing universally familiar benchmark datasets and metrics for pavement crack detection. Additionally, defining diverse crack types more simply would lead to a higher information of the trouble and extra effective model improvement. This ought to open possibilities for standardized benchmarking and decorate the ability to evaluate the strengths and weaknesses of different fashions.

V. CONCLUSION

Deep learning has emerged as a powerful tool for automated characteristic extraction throughout various complicated records environments. This analysis covers numerous programs, which includes urban morphological similarity, constructing footprint extraction, and general advancements in deep getting to know. Key findings are summarized below, highlighting the effectiveness, challenges, and future guidelines for each place.

Key Findings
Urban Morphological Similarity Analysis:

- **Approach:** Utilized GoogLeNet with inception-v3 to encode city morphology into feature vectors.
- **Outcome:** Enabled specific multi-dimensional case retrieval, integrating morphological and infrastructural similarities for stepped forward decision-making.
- **Challenges:** Future enhancements include including more dimensions to the dataset and exploring geometric spatial information for better accuracy.

Building Footprint Extraction:

- **Approach**: Applied DeepLabv3 for semantic segmentation of building footprints from far flung sensing pictures.
- **Outcome:** Achieved promising consequences notwithstanding noisy records, with a workflow involving statistics preprocessing, modeling, and postprocessing.

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- **Challenges:** Issues include irregular building shapes and discrepancies among ground fact and remote sensing facts. Future paintings will consciousness on refining postprocessing, integrating Lidar facts, and improving model robustness.

General Deep Learning Advancements:

- **Approach:** Reviewed the evolution from conventional ANNs to advanced deep getting to know strategies.
- **Outcome:** Demonstrated deep learning's fulfillment in numerous packages like image recognition, biometrics, and NLP.
- **Challenges**: Key challenges are interpretability and reasoning. Future studies need to address these problems to increase greater transparent and powerful fashions.

Aspect	Urban Morphological Similarity	Building Footprint Extraction	General Deep Learning Advancements
Data and Method	3817 residential cases, GoogLeNet with inception-v3 module	DeepLabv3+ algorithm, remote sensing images	Overview of ANNs and deep learning evolution
Key Techniques	2048-dimensional feature vectors, Euclidean distance for similarity	Semantic segmentation, GIS-format conversion	Advanced deep learning methods and breakthroughs
Main Findings	Feasibility of DL in morphological analysis, multi-dimensional retrieval	Promising results despite noisy data, challenges in shape accuracy	Successful applications in image recognition, NLP, and more
Challenges	Need for more dimensions and precise inputs	Irregular building shapes, noise in data	Interpretability and reasoning issues
Future Directions	Integrate additional dimensions, explore geometric spatial data	Improve postprocessing, integrate Lidar data	Enhance model transparency, address interpretability issues

The application of deep getting to know architectures for feature extraction in complicated statistics environments famous vast advancements and ability. In city morphological similarity evaluation and building footprint extraction, deep mastering techniques have validated effectiveness in coping with complex datasets and providing valuable insights. Challenges inclusive of statistics noise and model interpretability stay, but ongoing research and technological upgrades keep promise for overcoming these troubles. Future paintings must cognizance on refining models, integrating numerous information sources, and addressing present obstacles to maximise deep mastering's impact throughout numerous packages.

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VI. REFERENCE

1. Kropf, K. Aspects of urban form. Urban Morphol. 2009, 13, 105.

2. Hemphill, L.; Berry, J.; McGreal, S. An indicator-based approach to measuring sustainable urban regeneration performance: Part 1, conceptual foundations and methodological framework. Urban Stud. 2004, 41, 725–755

3. Rossi, A.; Eisenman, P.; Ghirardo, D.Y.; Ockman, J. The Architecture of the City; MIT Press: Cambridge, MA, USA, 1982.

4. Chen, F. Urban Morphology and Citizens' Life. In Encyclopedia of Quality of Life and Well-Being Research; Springer: Dordrecht, The Netherlands, 2014; pp. 6850–6855.

5. Osman, T.; Divigalpitiya, P.; Osman, M.M.; Kenawy, E.; Salem, M.; Hamdy, O. Quantifying the relationship between the built environment attributes and urban sustainability potentials for housing areas. Buildings 2016, 6, 39.

6. Sarralde, J.J.; Quinn, D.J.; Wiesmann, D.; Steemers, K. Solar energy and urban morphology: Scenarios for increasing the renewable energy potential of neighbourhoods in London. Renew. Energy 2015, 73, 10–17

7. ASCE. American Society of Civil Engineers (ASCE) 2017 Infrastructure Report Card: Roads; American Society of Civil Engineers (ASCE): Reston, VA, USA, 2017

8. Flintsch, G.; McGhee, K. NCHRP Synthesis 401: Quality Management of Pavement Condition Data Collection; Transportation Research Board: Washington, DC, USA, 2009

9. Tsai, Y.; Wang, Z. Development of an Asphalt Pavement Raveling Detection Algorithm Using Emerging 3D Laser Technology and Macrotexture Analysis; Final Report NCHRP IDEA Project 163; Transportation Research Board: Washington, DC, USA, 2015.

10. Wang, K.C.P.; Li, Q.J.; Yang, G.; Zhan, Y.; Qiu, Y. Network level pavement evaluation with 1 mm 3D survey system. J. Traffic Transp. Eng. Engl. Ed. 2015, 2, 391–398.

11. Robinson, C.; Hohman, F.; Dilkina, B. A deep learning approach for population estimation from satellite imagery. In Proceedings of the 1st ACM SIGSPATIAL Workshop on Geospatial Humanities, New York, NY, USA, 7–10 November 2017; pp. 47–54.

12. Rodriguez, A.C.; Wegner, J.D. Counting the uncountable: Deep semantic density estimation from space. In German Conference on Pattern Recognition; Springer: Cham, Switzerland, 2018; pp. 351–362

ISSN:2731-538X | E-ISSN:2731-5398
Vol. 18 No. 02 (2024)

13. Chen, Y.; Hong, T.; Luo, X.; Hooper, B. Development of City Buildings Dataset for Urban Building Energy Modeling. Energy Build. 2019, 183, 252–265.

14. Yu, M.; Yang, C.; Li, Y. Big data in natural disaster management: A review. Geosciences 2018, 8, 165

15. Cerovecki, A.; Gharahjeh, S.; Harirchian, E.; Ilin, D.; Okhotnikova, K.; Kersten, J. Evaluation of Change Detection Techniques using Very High Resolution Optical Satellite Imagery. Preface 2015, 2, 20.

16. Arel, I.; Rose, D.C.; Karnowski, T.P. Deep machine learning—A new frontier in artificial intelligence research [research frontier]. IEEE Comput. Intell. Mag. 2010, 5, 13–18

17. Benos, L.; Tagarakis, A.C.; Dolias, G.; Berruto, R.; Kateris, D.; Bochtis, D. Machine Learning in Agriculture: A Comprehensive Updated Review. Sensors 2021, 21, 3758.

18. Huang, J.; Chai, J.; Cho, S. Deep learning in finance and banking: A literature review and classification. Front. Bus. Res. China 2020, 14, 13.

19. Gambella, C.; Ghaddar, B.; Naoum-Sawaya, J. Optimization problems for machine learning: A survey. Eur. J. Oper. Res. 2021, 290, 807–828.

20. Yuan, F.-G.; Zargar, S.A.; Chen, Q.; Wang, S. Machine learning for structural health monitoring: Challenges and opportunities. Sens. Smart Struct. Technol. Civ. Mech. Aerosp. Syst. 2020, 11379, 1137903