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Pattern Recognition Methods for Remote-Sensing-Based Land Use and Land Cover Analysis

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Abstract: Pattern recognition is critical for obtaining useful informationfromremotesensingdataandimprovingland-use and land-cover (LULC) classification. With the increased availability of multispectral, hyperspectral, LiDAR, and high-resolution data, sophisticated algorithms are needed to address issues such spectral similarity, geographical heterogeneity, at-mospheric distortions, and mixed pixels. Recent research has shown that machine-learning models such as SVM, Random Forest, Ensemble Learning, and ELM, as well as deep-learning architectures such as CNNs, U-Net, and hybrid spectral-spatial networks, improve classification accuracy and environmental monitoring. Semantic alignment, open-vocabulary mapping, spatial point pattern analysis, and novel-class discovery are all emerging technologies that promote adaptability in dynamic contexts. The use of GIS, Monte Carlo simulations, and mul-timodal data fusion improves the modelling of environmental processesandlong-termchanges.Overall,thereviewedresearch demonstrate that sophisticated pattern-recognition approaches offerdependable,scalable,anddata-drivensolutionsforremote-sensing applications, thereby promoting sustainable resource management, urban planning, ecological conservation, and climate-resilient development.
Keywords -Pattern Recognition, Remote Sensing, Land Use and Cover (LULC), Hyperspectral Imaging, Open Vo-cabulary Mapping, Spatial Point Pattern Analysis, GIS, Monte Carlo Simulation, and Environmental Monitoring.

I. INTRODUCTION

The tremendous rise in remotely sensed data broughtabout by the quick development of Earth observation tech-nologiespresentsbothnewopportunitiesanddifficulties for the analysis of land-use and land-cover (LULC) trends. Withtheabilitytoautomaticallyextractusefulinforma-tion from multispectral, hyperspectral, LiDAR, and high-resolutionsatellitedata,patternrecognitionhasbecomeakey technique in remote sensing. Pattern recognition techniques, incontrasttoconventionalmanualinterpretationapproaches, can effectively manage massive amounts of diverse data, facilitatemulti-temporalanalysis,andenhanceenvironmental monitoring accuracy.

Remote-sensingimagesfrequentlyincludehighspectralsim-ilarity between classes, spatial heterogeneity, atmospheric aberrations,andmixedpixels,whichcomplicateclassification and change detection tasks. To address these issues, re-searchershavedevelopedadvancedapproachesthatcombine spectral, spatial, textural, and temporal features, which are supported by machine-learning algorithms such as Support Vector Machines (SVM), Random Forest (RF), Ensemble Learning,andExtreme LearningMachines(ELM),aswellas deep-learning models such as CNNs, U-Net, and hybrid 2D-3Dnetworks,allofwhichsignificantlyimproveclassification robustnessandprecision.Recentadvancesgobeyondtypical closed-setclassificationtoincludesemanticalignment,open-vocabularymapping,spatialpoint-patternmodelling,andthe development of novel land-cover classes in fast changing metropolitan situations. Furthermore, the ability to model environmentalprocesses, evaluateradiation exposure, analyse ecological relationships, and forecast long-term landscape dynamics has improved due to the integration of GIS, Monte Carlo simulation frameworks, and multimodal data fusion. All things considered, pattern recognition provides a thor-ough and scalable framework for obtaining high-quality data from remote-sensing datasets, supporting essential applica-tions in urban planning, ecological conservation, disaster management, climate-resilient development, and sustainable resource monitoring. This study expands on these develop-ments by examining current approaches and proving their efficacy in enhancing the dependability of LULC mapping and environmental analysis.

II. LITERATURE SURVEY

Leila M.G. Fonseca et al. [1] undertook a thorough investigation on the use of pattern recognition and remote sensing techniques for mapping Land Use and Land Cover (LULC) in the Brazilian Savannah, often known as the Cerrado biome.

The study sought to address the growing issues of sustainable land management in this critical ecological area, which is characterised by fast agricultural development and deforestation.

The researchers used pattern recognitionandimageprocessingtoolstoinvestigatehow natural vegetation transformed into agricultural and pasture lands during a 20-year period. Their method merged standardpixel-basedclassifierssuchasMaximumLikelihood Classification (MLC) and Spectral Angle Mapper (SAM) with object-based algorithms that employed Geographic Object-Based Image Analysis (GEOBIA) to increase spatial andcontextualaccuracy.Theyalsoemployedmulti-temporal classification with Satellite Image Time Series (SITS) datato identify seasonal shifts and minor land-cover transitions. To improve classification performance, the study used machinelearningmethodssuchasRandomForest(RF) and Support Vector Machines (SVM), as well as deep learning models like U-Net, to segment satellite pictures. Thesetechniquesdemonstratedgreataccuracy,withRandom Forest achieving up to 93% accuracy in pasture mappingand deep learning models reaching around 95% accuracy in identifying deforestation. The study used textural features from the Gray-Level Co-occurrence Matrix (GLCM) as well as phenological metrics from dense Landsat and Sentinel time series to classify vegetation types and crop patterns.Theauthorsalsoincorporated environmentaldatasetssuchastopography,soiltype,anddrainagenetworksinto their classification procedures, demonstrating that combining contextual features with spectral and temporal datadramaticallyimprovedland-covercategorisation. Thefindingsdemonstratedthesuccessfulidentification and mapping of various vegetation types, pasture kinds, agriculturalmethods,anddeforestationratesthroughout the Cerrado. However, the study identified persistent issues such as spectrum confusion in transition zones, cloud interference, and data imbalances between vegetation classifications. Fonseca et al. stated that hierarchical classification frameworks, time-series analysis, and context-awaresegmentationarethemostpromisingapproachesfor future LULC mapping. They emphasised the need for hybriddeeplearningsystemsthatcombinegeographical and temporal data, such as CNN-LSTM models, to improve scalability and resilience while monitoring broad areas. Overall, their findings demonstrated that integrating pattern recognition and remote sensing enables for accurate and long-term monitoring of environmental changes in complex biomes such as the Brazilian Cerrado, which can aid in improved policymaking and ecological conservation efforts.

Haoyan Xie et al. [2] did extensive research on applying pattern recognition techniques to categorise land-cover remote-sensingphotos.Theirstudysoughttoincrease theaccuracyofremote-sensingpicturecategorisationby addressing the limitations of standard pixel-based approachesthatrelysolelyonspectraldata.Tomanage the complexity of remote-sensing data, the researchers created a powerful hybrid system that integrates machine vision, statistical analysis, and machine learning algorithms. The authors applied both supervised and unsupervised classification algorithms on high-resolution satellite photos fromNanjing’sYuhuataiDistrict(2018-2019),whichhad a spatial resolution of 2.5 meters. They used a variety of methods, including Maximum Likelihood Classification (MLC), Support Vector Machines (SVM), Decision Tree (C5.0), Fuzzy C-Means (FCM) clustering, and ensemble techniques combining Extreme Learning Machines (ELM) andSVM.TheEnsemble-ELMmodelsignificantlyimproved classification performance on the PaviaU dataset, with an overallaccuracy(OA)of91%andaKappacoefficientof 0.88. This resulted in a nearly 20% improvement over normalELManda10%increaseoverSVMclassifiers. The Indian Pines dataset achieved an overall accuracy of 86.2%, with a 13% improvement in average accuracy (AA) and a Kappa score of 0.84. However, with the Salinasdataset, the improvement was moderate at around 5%, indicating performance variability depending on the dataset. Theauthorsalsoinvestigatedoptimisingkernelfunctions in SVM and proposed two new strategies for improvingnoise resistance and parameter flexibility. The combination of FCM segmentation with SVM classification significantly decreased the ”salt-and-pepper” effect seen in pixel-based classifications.Beyondalgorithmicbreakthroughs,the work established object-oriented image analysis (OBIA) principles, which enable context-aware categorisation by combining spatial, textural, and geometric characteristics. Thisstrategyimprovedtherecognitionofcomplicated land-cover categories such urban structures, vegetation,waterbodies,andbaresoil.ThestudyalsousedLCNet-27, a convolutional neural network-based model that enhanced accuracyviamulti-scalefeatureextractionandtexturefusion. The authors demonstrated that deep learning architectures such as LCNet-27 outperform traditional SVM and ELM models when trained on spectral-textural inputs, resulting in smoother classification maps with fewer misclassifications. Xie et al. stated that when paired with ensemble and deep learning approaches, pattern recognition provides a powerful framework for remote-sensing image classification. Their researchdemonstratedthesignificanceofcombiningspectral, spatial,and texture features for effectiveland-cover analysis. To improve classification accuracy and generalisability, they proposed further research into hybrid models that combine CNNs, SVMs, and ELMs, as well as data-fusion techniques that use multispectral and hyperspectral sources. Overall, their findings represent a significant step forward in the modernisation of remote-sensing classification and will lead to smarter, automated systems for accurately mapping land cover.

Thomas U. Omali et al. [3] investigated the use of pattern recognition (PR) techniques to remote sensing picture processing. They demonstrated how these strategies increase the accuracy of land-use and land-cover categorisation (LULC). Their research combines theoretical underpinnings withpracticalapplicationstoanalyseenvironmental changesovertime.Toensurehigh-qualityanalysis,the authors developed a methodical PR procedure that included pattern capture, picture preprocessing, feature extraction, classification/regression, and post-processing. They employed preprocessing techniques such geometric correction to remove spatial distortions, radiometric correctiontominimisesensorandambientnoise,andpan-sharpeningtoincreaseimageresolution.Thestudyused both supervised and unsupervised classification approaches using multitemporal Landsat images collected between 2015 and 2020 to identify six broad land-cover classes: dense vegetation,sparsevegetation,barrenland,built-uparea,rock outcrop, and agriculture. Their findings revealed major land-coverchanges.Built-upareasincreasedfrom30.69%in2015 to 38.57% by 2020, whereas sparse vegetation decreased from26.14%to21.99%.Thissuggeststhaturbanisation and vegetation loss will continue. The study's accuracy evaluation indicated that supervised classification gave more reliable findings thanks to well-defined training samples. OmaliandUmoruemphasisedthatpatternrecognition offers a systematic, data-driven framework for recognising environmental patterns and tracking landscape changes.They concluded that integrating pattern recognition withGIS considerably enhances land-cover mapping precisionand clarity. In order to acquire more reliable and automated remote sensing analysis, they also advised adopting machine learning techniques such as Random Forest, SVM, and deep learning models in future study.

Xibo Ma et al. [4] created a thorough, region-sensitive methodologythatintegratesMonteCarlosimulations,GISanalysis,andremote-sensingdatasetstoforecast indoor gamma-ray dosage location factors (LFs) afterground deposition of 137 Cs. Their goal was to satisfy the increasing need following nuclear accidents like Fukushima and Chernobyl for precise, spatially explicit dose prediction. In order to represent urban and land-cover characteristics such as building density, vegetation cover, and permeable-surface fractions that have a significant impact on indoor radiation attenuation, the authors developed the Local RadiationEnvironmentZone(LRZ)classification,which is based on the well-known Local Climate Zone (LCZ) framework. They produced dose-distance response matrices for combinations of LRZ types using PHITS-based Monte Carlophoton-transportsimulations,takingintoconsideration variationsinshieldingenvironmentsandbiologicalhalf-lives of pollutants on soil versus paved surfaces. They createdLRZ maps by preprocessing multispectral Landsat images andGISlayers.Thesemapsledthedistributionofsimulation results to actual geographic locations, allowing for spatially resolved LF estimation over time for both first- and second-floor indoor environments. The study's findings showed significant temporal and regional fluctuations in indoor LFs, which were caused by variations in building morphology, land-cover types, and the environmental behaviour of deposited 137Cs. Sparately constructed and vegetated areas showed greater initial doses, whereas compact urban zones showed lower LFs due to stronger shielding from densely built structures. Long-term exposure patterns are strongly impactedbyecologicalhalf-lifedifferencesbetweensoiland concretesurfaces,accordingtotemporalassessments.Strong qualitative agreement with available measurement datasets andearliermodellingresearchwasdemonstratedbytheLF maps produced by the combined simulation–GIS technique. Notwithstanding its advantages, the authors pointed outsome drawbacks, such as oversimplified building material assumptions,theomissionofcomplicatedtopography,and errors in real deposition patterns. They suggested improving deposition inputs, using a variety of building kinds, and refining LRZ criteria in future study. All things considered, this approach offers a scalable, scientifically based instrument for post-accident radiation assessment, assisting with public health risk management, emergency response, and long-term relocation planning.

Zermatten et al. [5] investigated the limitations and practical problems of employing classical deep-learning modelsforland-covermapping,particularlywhenapplied to real-world remote-sensing datasets with varying class definitions and nomenclatures. They recognised thepotential of high-resolution aerial photography and current segmentation architectures for enhancing land-cover prediction, but said that little progress had been made towards true semantic flexibility or interoperability between datasets.Theyidentifiedtwomajorissues:first,most land-cover models are trained using rigid, fixed label sets, which means the model learns class names as isolated categories rather than semantic concepts; and second, even well-trainedsupervisedmodelsdonottransfereffectively to new regions or datasets because of variances in label nomenclature, class hierarchy, and local definitions, the learntrepresentationsarenotgeneralisable.Toaddress these challenges and guide future research, the authors developed the TACOSS framework, which incorporates language-driven semantic alignment into open-vocabulary land-covermapping.Insteadofusingpredefinedlabels, the Text-Aligned component defines classes semantically using natural-language descriptions produced from encoders like as CLIP, GloVe, or SBERT. The Contrastive element matchespixel-levelvisualdatawithtextembeddings usingasupervisedcontrastivelossthatisaugmentedbya B-cos similarity function to boost discriminative ability.

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To represent real-world linguistic variation, the Contextual Semanticcomponentemploystext-augmentationtactics,such as expanding class descriptions with synonyms and different wording.Finally,theOpen-VocabularySegmentationfeature allows the model to react to any text queries and Harmonise labelsacrossdatasets,addressingtheongoingproblem of mismatched taxonomies. The authors advocated for ashift away from solely label-dependent supervised models and towards models that demonstrate a clear, semantically grounded alignment of language and visual features. They contended that by combining language semantics and text augmentation, remote-sensing systems can generate more adaptable, transportable, and practically usable land-cover models. Their findings indicate that, while TACOSS loses some closed-set accuracy, it enables robust cross-dataset applicationandconstitutesanimportantsteptowards operational,interoperableland-covermapping.

Jing Du et al. [6] introduced Land Cover Discovery Mapping (LCDM) and 3DLCDM, an end-to-end hybrid-supervisionframeworkintendedtoidentifyandmap newurbanland-coverclassesfrom3Dpointclouds. LCDMismotivatedbytheauthorsobservationthat quickly changing urban surroundings generate previously unannotated characteristics (adaptive fac¸ades, temporary fixtures,renewableenergyinstallations,etc.)thatstatic label sets are unable to capture. In order to address this, 3DLCDMcombinesunsupervisednovel-classdiscoverywith full supervision for known classes: a shared MinkUNet34C backbone extracts features that feed a supervised head for labelled categories and a dual unsupervised head (a primary fixed-prototype branch plus an over-segmentation branch with progressive prototype scheduling) for unknown classes. The method mitigates the severe class imbalance typical of urban point clouds by using a dynamic weighting technique (batch + global momentum) and temporal Sinkhorn–Knopp normalisation with adaptive temperature scheduling to produceresilientpseudo-labels.Inordertomakethe method scalable to large 3D datasets, the study describes preprocessingandblock-partitioningmethodologiesfor twotestbeds(DALESandH3D),voxelizationsettings, and training/inference procedures. The practical value of 3DLCDM is demonstrated by experimental results, which show that the method significantly improves novel-class mIoU(upto+16.95%onDALESand+24.43%onH3D) across multiple base/novel splits and preprocessing protocols, while also boosting base-class and overall mIoUincomparisontostrongbaselines(NOPS,CHNCD).Detailed split-level results demonstrate significant gains for difficult withheld classes (e.g., ground, cars, low vegetation, impervious surfaces), and qualitative visualisations confirm superior boundary delineation and finer feature discovery; ablation studies validate superior boundary delineation. The authors also examine computational trade-offs (voxelization, partitioningstrategies)andvalidaterobustnessacrossdatasets (DALES, H3D, SemanticPOSS) and partitioning schemes, highlighting 3DLCDM's preparedness for operational land-cover discovery mapping in changing urban environments.

Sangeetha et al. [7] presented a complete review of hyperspectral image (HSI) classification techniques. They focused on the challenges that high-dimensional spectraldata create and the improvements in feature extraction and band-selectionstrategies.Theirapproachaddressedthe main drawbacks of conventional pixel-based classifiers, which frequently experience classification noise in varied landscapes,spectralredundancy,andtheHughesphenomena. The authors looked at popular public datasets, such as Indian Pines, Pavia University, Salinas, Houston, and Botswana, emphasising their spectral properties and applicability in evaluatingcontemporaryclassifiers.Thestudyoffereda thorough analysis of dimensionality reduction techniques, including nonlinear approaches like kernel PCA, manifold learning,t-SNE,andautoencoder-basedmodels,aswellaslinearapproacheslikePCA,ICA,LDA,MNF,and NMF. Unsupervised band-selection techniques were given special attention, especially clustering-based methods,which have been demonstrated to successfully reduce redundancy while maintaining spectral bands with a wealth of information. The study also emphasised the increasing trend of spectral-spatial classification frameworks, pointing outthatsceneswithhighspatialcomplexityaredifficult for solely spectral models. Effective methods for capturing spatial texture and structure included morphological profiles, superpixel segmentation, GLCM, Gabor filters, LBP, and3Dtransforms.Recentdeeplearningdevelopments,such as2DCNNs,3DCNNs,hybrid2D+3Darchitectures, graph convolutional networks (GCNs), attention-based transformers, and hypergraph models, were found to be the main drivers of state-of-the-art classification performance on benchmark datasets. According to their survey, hybrid and deep learning models beat conventional classifiers like SVM and Random Forest, achieving nearly flawless accuracy on datasets like Pavia University and Salinas. The scientistsalso examined end-to-end spectral-spatial fusion networks, evolutionary and swarm-based band-selection methods, and ensemble approaches, highlighting the importance of spatial-context modelling and efficient dimensionality reduction for better performance. Limited labelled samples, atmospheric variability, mixed pixels, and the high computing cost of transformer-basedmodelsaresomeofthemajorissuesnoted. Inordertoimproveresilienceacrossdatasets,theysuggested future avenues include explainable AI, multimodal fusion with LiDAR/SAR, lightweight real-time architectures, and transfer learning. Overall, the study shows that the accuracy ofland-covercategorisationissignificantlyincreased when band selection, spectral-spatial characteristics, and sophisticated deep networks are combined.

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Costaetal.[8]conductedadetailedstudyonthe cooling effectiveness of Nature-Based Solutions (NBS).They used remote-sensing indices and machine-learning prediction models. By addressing the shortcomings of conventional land-surface temperature (LST) calculations, which frequently ignore spatial context and land-cover interactions, their research sought to improve the accuracyof urban heat assessments. In order to model the relationship betweenland-coverpatternsandthermalbehaviour,thestudy created a solid framework that integrated spatial measures, ensemblelearningalgorithms,andremote-sensingindicators. Using Landsat-8 data of the Guimara˜es region from 2014 to 2023, the authors calculated important indices such NDVI, NDBI,andGNDVIinadditiontoelevation,distancetoroads and streams, and NBS effect zones. To forecast current and near-future land-surface temperatures, these variables were includedtomanymachinelearningmodels,suchasRandom Forest (RF), XGBoost, Bagging Regressor, AdaBoost, andK-Nearest Neighbour (KNN). With a R^2 of 0.957, XGBoost outperformed RF (0.942) and Bagging (0.946) as the tested model with the highest predictive accuracy. With a Kappa of 0.873 and a total accuracy of 91.7%, Random Forest's land-cover classification was also dependable. The MOLUSCE CA-ANNmodelprojectedfutureland-coverchangeswith a Kappa of 0.894, showing stable transitions and growing NBS influence on urban temperatures. Despite slight offsets, the study also verified good relationships between ground-measured air temperature and satellite-derived LST. Overall, the authors point out that using sophisticated machine learning models in conjunction with spatial-context data, including proximity to vegetation, greatly enhances thermal predictionandpromotesclimate-resilienturbandevelopment.

Kosarevych et al. [9] conducted a study on improving environmental remote-sensing analysis by combining convolutional neural networks (CNNs) with spatial point-patternanalysis(SPPA).Thegoaloftheirresearchwasto overcome the shortcomings of conventional remote-sensingprocedures,whichfrequentlyonlyusepixel-based classification and are unable to record ecological interactions across different landscapes. In order to closethis gap, the scientists presented a unique system that uses CNN architectures (EffNet and LeNet) to first classify remote-sensing picture patches. The identified outputs are thenconvertedintomarkedspatialpointpatternsthat reflect various land-cover kinds. One of the study's main innovations was a new data-augmentation technique basedon spatiotemporal similarity, which expanded the training datasetbyusingseveralsatellitephotostakenoverthe same area at various times. This method demonstrated its appropriateness for remote-sensing contexts with minimal labelled data by improving classification accuracy by more than 7% when compared to typical augmentation techniques. The authors demonstrated through extensive tests utilising Landsat-8imageryoftheShatskNationalNaturePark that,withthebackingofhuge,enricheddatasets,even basicCNNarchitecturesmayachievehighaccuracy(up to97%top-1).Usingsecond-orderstatistics,suchas K-functions,g-functions,andmark-correlationmetrics,the produced point-pattern maps allowed for a thorough ecological interpretation that revealed interactions like the proximity of forests to water and the spatial exclusion between forested and built-up areas. Their findings showed that point-pattern representation may simulate interspecificorinterclassinteractionsatvariousgeographicalscales and captures ecological complexity more successfully than conventional raster-only techniques. The work highlighted the wider potential of integrating deep learning with SPPAtoidentifybioticlinkages,trackhabitatchanges,andprovide ecosystem-level analysis in addition to classification. Future research needs, such as incorporating sophisticated CNN models,enhancingzero-modelpoint-processformulations, andcreatingmorereliableframeworksfordynamic ecological processes, were underlined by the authors.

Alawodeetal.[10]conductedathoroughstudyof land-use and land-cover (LULC) changes in the Mo¨dling municipalityofAustria.Theyuseda24-yearcollectionofLandsat-7ETM+andLandsat-8OLI/TIRSimagesfrom1999to2022.Theirmaingoalwastoproduce preciseLULCmapsatthemunicipalitylevelthatget around the drawbacks of regional datasets with coarse resolution, like CORINE. In order to accomplish this, the scientists developed a reliable remote-sensing workflow that includes sun-angle normalisation, radiometric correction,top-of-atmosphere reflectance conversion, and Maximum Likelihood supervised classification. High classification reliability was assured by extensive ground-truthing utilising GPS coordinates, orthophotos, Google Earth sampling, and CORINE comparison. With total accuracies ranging from 91.9%to94.4%andKappacoefficientsbetween0.897 and 0.929, the produced LULC maps showed excellent performance, demonstrating the efficacy of combining supervisedclassificationwithGIS-basedspatialanalysis for local environmental monitoring. The study assessed vegetationdynamicsusingNDVIandSAVIinadditionto LULC mapping, allowing for a comparison between supervisedforestclassificationsandindex-basedpredictions. The authors discovered that whereas SAVI continuously overstated forest cover, NDVI closely matched supervised forest patterns, indicating the sensitivity of soil-adjusted indices in peri-urban environments with fragmented vegetation.Significantland-coverchangeswereidentifiedby the multi-temporal analysis: built-up areas rose significantly (by more than 1,500 hectares) due to persistent urbangrowth, while forest cover decreased by 2.61 percentage points(about743hectares).Theseresultsdemonstrate howsettlementgrowthisputtingincreasingstrainon natural and semi-natural regions.

The study showed how remotesensingandGIStogetherprovideathorough, useful understanding of landscape change by combining multi-temporal Landsat data, pixel-level post-classification comparison,andvegetation-indexanalysis.Thisprovidesa useful evidence base for urban planning, conservation strategies, and long-term environmental management in rapidly urbanising regions.

III. CONCLUSION

This study emphasises how important pattern recognition isforincreasingremotesensingdataprocessingandland-use and land-cover (LULC) categorisation accuracy. It is clear from the reviewed works that combining spectral, spatial, textural, and temporal features with contemporary machine-learning and deep-learning techniques greatly improves classification performance, lowers noise, and facilitatesmore accurate interpretation of complex landscapes. The shortcomingsofconventionalclosed-setsystemsarefurther addressed by emerging techniques like semantic alignment, open-vocabularymodels,spatialpoint-patternanalysis,and novel-class discovery, which provide more flexibilityfor practical applications. Understanding environmental processes, radiation exposure, ecological interactions, and landscape dynamics is further improved by the integrationof GIS, Monte Carlo simulations, and multimodal data fusion. All things considered, recent developments in pattern recognition offer robust, scalable, and data-driven solutions for remote sensing analysis, promoting climate resilience, ecological conservation, sustainable urban development, and well-informeddecision-making.Theliterature'sobservations show that sustained innovation in this area will be crucial for addressing upcoming environmental issues and enhancingthe accuracy of LULC mapping.

REFERENCES

[1] L. M. Fonseca, T. S. Ko¨rting,H. d. N. Bendini, C. D.Girolamo-Neto,A. K. Neves, A. R. Soares, E. C. Taquary, and R. V. Maretto, "Patternrecognitionandremotesensingtechniquesappliedtolanduseandlandcover mapping in the brazilian savannah," Pattern recognition letters,vol. 148, pp. 54–60, 2021.

[2] H. Xie and H. Huang, "Classification of land cover remote-sensingimages based on pattern recognition," Scientific Programming, vol.2022, no. 1, p. 8319692, 2022.

[3] T. U. Omali and K. Umoru, "Pattern recognition in remote sensingimage analysis: Theory, methods, and a case study of rijiyar donor inkatsina,nigeria,"Int.J.Sci.Res.inComputerScienceandEngineeringVol, vol. 11, no. 6, 2023.

[4] X. Ma, Z. Wang, Y. Ishida, and H. Kobayashi, "Land-cover-basedindoor gamma-ray dose after a nuclear accident: location factor map-ping via monte carlo simulation, gis, and remote sensing," Journal ofEnvironmental Radioactivity, vol. 291, p. 107853, 2026.

[5] V. Zermatten, J. Castillo-Navarro, D. Marcos, and D. Tuia, "Learningtransferable land cover semantics for open vocabulary interactionswith remote sensing images," ISPRS Journal of Photogrammetry andRemote Sensing, vol. 220, pp. 621–636, 2025.

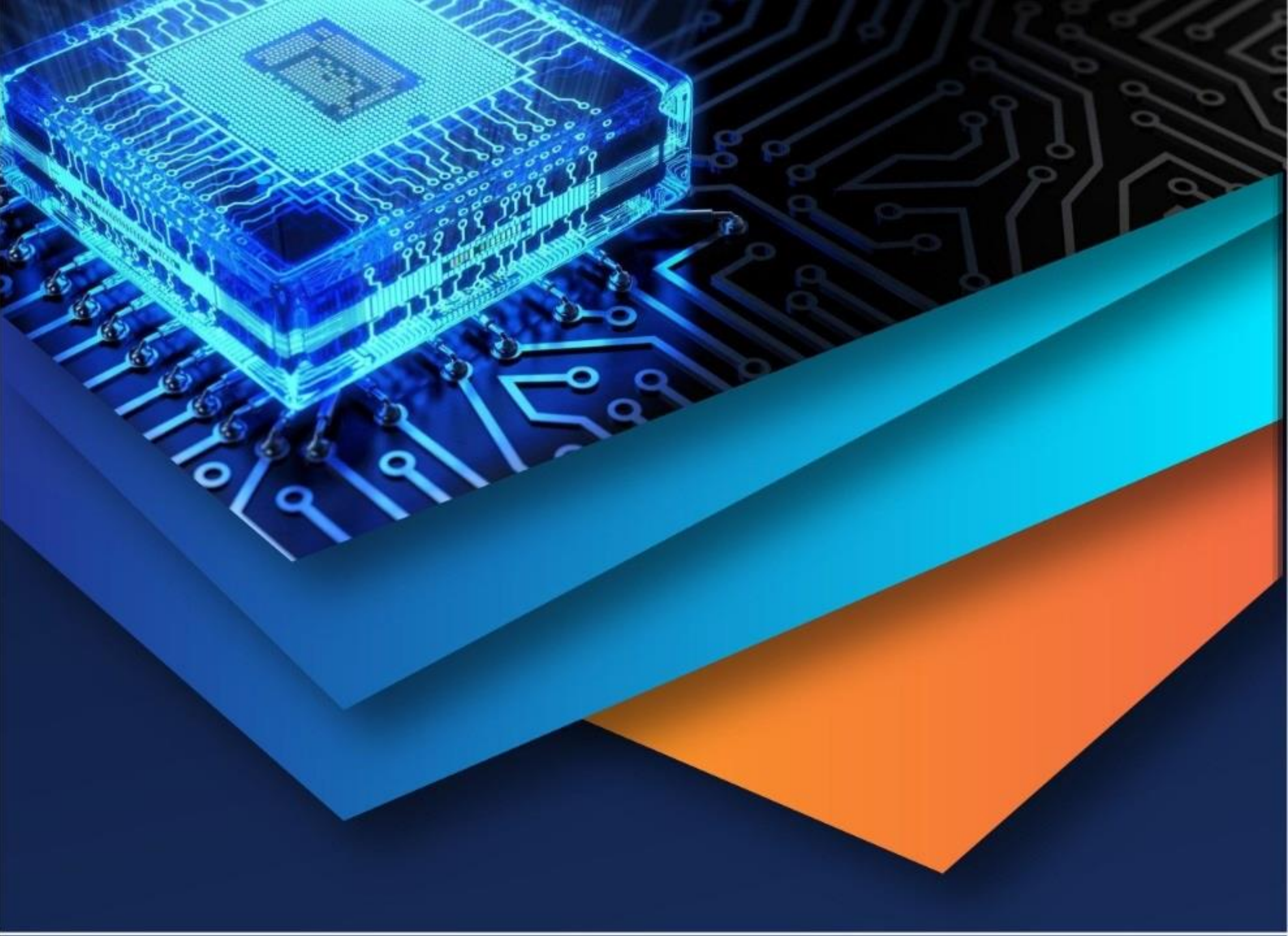
[6] J.Du,J.Zelek,D.Zhang,andJ.Li,"3dlcdm:Hybridsupervisionfor land cover discovery mapping of emerging urban structures in 3dremotesensing,"RemoteSensingofEnvironment,vol.331,p.115018,2025.

[7] V. Sangeetha and L. Agilandeeswari, "Artificial intelligence enabledspectral-spatial feature extraction techniques for land use and landcover classification using hyperspectral images–an inclusive review,"The Egyptian Journal of Remote Sensing and Space Sciences, vol. 28,no. 3, pp. 455–467, 2025.

[8] P.C. Toscan, K. Seong, J. Jiao, C.A. L. R. Ribeiro, F. A. C.Carvalho,M. L. Oliveira, and E. B. Pereira, "Impact of nature-based solutions(nbs) on urban surface temperatures and land cover changes usingremote sensing and machine learning," Remote Sensing Applications:Society and Environment, p. 101721, 2025.

[9] R. Kosarevych, O. Lutsyk, B. Rusyn, O. Alokhina, T. Maksymyuk,andJ.Gazda,"Spatialpointpatternsgenerationonremotesensingdatausing convolutional neural networks with further statistical analysis,"Scientific Reports, vol. 12, no. 1, p. 14341, 2022.

[10] G.L.Alawode,T.V.Oluwajuwon,R.A.Hammed,K.E.Olasuyi,A. Krasovskiy, O. C. Ogundipe, and F. Kraxner, "Spatiotemporalassessmentoflanduselandcoverdynamicsinmo¨dlingdistrict,austria,using remote sensing techniques," Heliyon, vol. 11, no. 11, 2025.



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