

DEEP LEARNING SOLUTIONS FOR AUTOMATED LANDSCAPE FEATURE MAPPING

GEOAI for managing and monitoring sustainable
farming, local habitat and landscape recovery

CONTENTS

Abstract	03
Shaping the Need for Smarter Land Monitoring	03
The Challenge: Addressing the Monitoring Gap	04
From Concept to Field: Proof-of-Concept Results	04
Business and Environmental Impact	09
Towards Scalable, Real-Time Landscape Intelligence	09
About the Author	09
About Cyient	10

Abstract

Cyient's LandSENS modules combine advanced GeoAI deep learning mapping models and earth observation data cubes to support targeted client land monitoring requirements across a range of sectors. Using a proof-of-concept approach to solution development, our automated mapping services develop custom pre-trained models for rapid, on-demand mapping and anomaly detection on newly acquired imagery.

Shaping the Need for Smarter Land Monitoring

Cyient Europe has been a trusted partner to a government agency in England responsible for agricultural payments and land management since 2007, delivering Digitisation and Integrated Geospatial Services. This Agency plays a central role in advancing sustainable farming practices and rural economic growth. Through new Environmental, it supports environmental goals such as biodiversity enhancement, carbon sequestration and soil conservation.

Accurate, large-scale, and continuous agricultural mapping is fundamental to these

initiatives, ensuring that policy decisions are informed by reliable, timely geospatial data.

Cyient has worked closely with the Agency to develop automated mapping solutions, applying innovative technologies such as deep learning to deliver detailed and accurate spatial outputs. In partnership with Picterra, we have conducted a series of proof-of-concept projects to design and refine GeoAI models capable of detecting and mapping critical agricultural features, including grass buffer areas, national cropped extents and nesting plots.



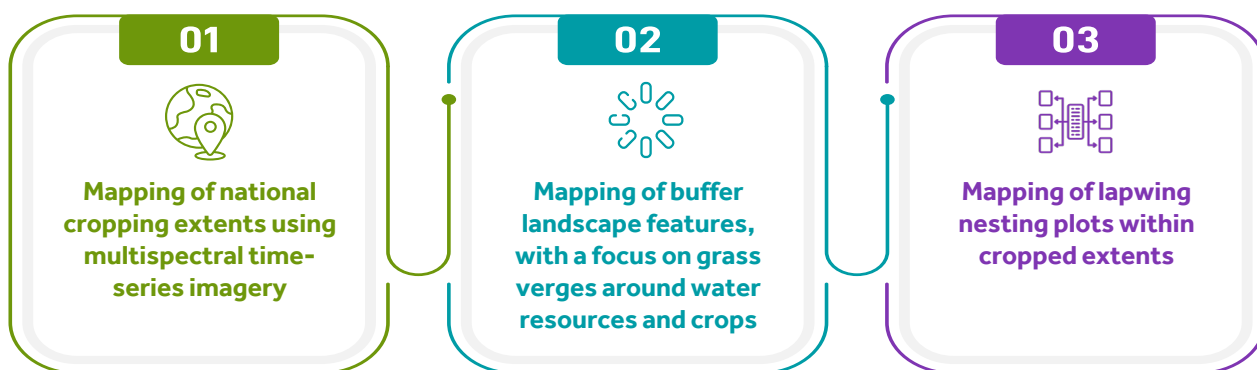
The Challenge

Addressing the Monitoring Gap

The Government Agency commissioned three phases of a proof-of-concept project with Cyient to assess the use of state-of-the-art deep learning models combined with new earth observation (EO) datasets for locating and mapping targeted landscape features.

Cyient's GeoAI-Driven Solution Framework

Three use cases where EO data and artificial intelligence-driven deep learning tools could add value:



Accurate mapping of national agricultural activity is crucial for informing policy, particularly in the context of the UK's new schemes. These mapped datasets help the Agency and its partners monitor farming practices, track environmental outcomes such as biodiversity and carbon sequestration, and administer incentives effectively.

Supervised machine learning methods using multi-temporal remote sensing data have been widely implemented in land-cover and land-use classification. However, advances in deep learning models, with increasingly accessible, high-resolution satellite data, create new

opportunities for accurate and cost-efficient mapping at scale. Deep learning models leverage historical datasets for automated pre-training, enabling stronger pattern recognition and the ability to capture complex non-linear relationships..

By reducing reliance on frequent and costly ground surveys, this approach supports faster, more resilient mapping processes and delivers accurate predictions of land features and habitats. The result: Improved monitoring and data-driven decision-making for agricultural policy and environmental management.

From Concept to Field: Proof-of-Concept Results

To train these models, thousands of feature examples were annotated, using Sentinel 2 10m multispectral data, APGB 25 cm aerial photography and high-frequency PlanetScope 3m data across varied geographies and seasonal conditions. Unlike traditional supervised classification methods, deep learning approaches enhance feature detection by leveraging advanced spectral and pattern-recognition techniques across multi-dimensional data cubes.

The Cyient team utilised a newly developed AI platform to train several deep learning models capable of identifying and mapping landscape features from satellite imagery. This approach focused on testing different EO data combinations, resolutions and processes to determine the most accurate mapping results for each use case.

National Crop Extent Mapping



Figure 1: Sentinel-2 imagery acquired in April 2020 in Northamptonshire (left), with crop extent model results for April-May-July overlaid (right). Yellow outlines are claimed crops, permanent grassland in white.

Binary maps corresponding to pixel-based crop and non-crop extents were produced to test the feasibility of mapping annual national cropping activity using Sentinel-2 10m multispectral data acquired at different points during the growing season.

Four deep learning models were trained for different month and spectral band combinations of Sentinel-2 data. The best performing models for selected test areas achieved accuracies of over 94% for classified crop maps using a single 'crop' class.

The ESA Copernicus Sentinel-2 mission provides freely available multispectral imagery at 10m resolution with a revisit rate of 3-5 days. Its combination of high temporal frequency with optical and near-infrared channels allows for time-series analysis of crop types and

extents, based on their spectral signatures at different points in the phenological stage of a crop.

A total of 43,555 cropped fields samples for April-May-July and 42,630 samples for June-July-August were used to train both models across eight Sentinel-2 imagery tiles.

Models pre-trained on time-series data for April, May and July including an additional NDVI band and the full 15-band 10m Sentinel-2 data, produced the most accurate classified results. The inclusion of an NDVI band, used to quantify vegetation 'greenness' or health, significantly improved crop identification, boundary definition within parcels, and discriminating larger grassland areas and grass verges within a field.

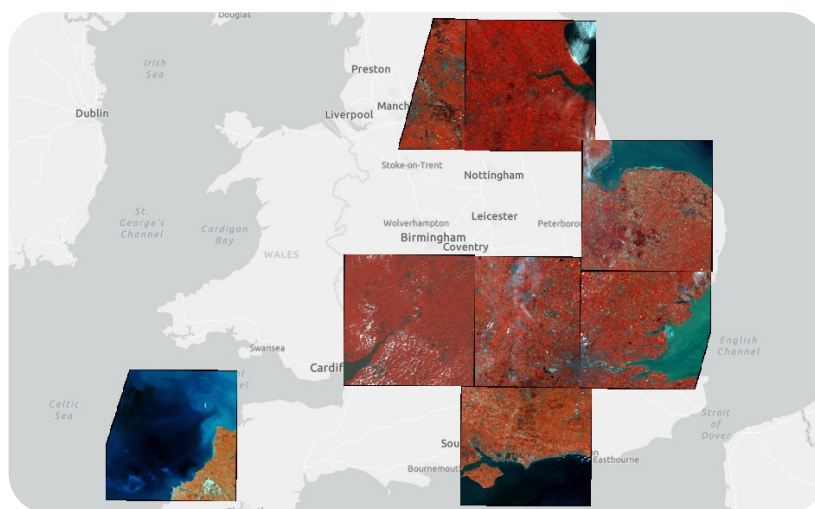


Figure 2: Sentinel-2 10m imagery tile stacks shown in false-color. Each tile includes bands for blue (B2), green (B3), red (B4), near-infrared (B8) channels and an NDVI band at 10m resolution for three-month timestamps.

Mapping Natural Buffers and Vegetation Features

Within schemes, the mapping and monitoring of finer scale vegetation and agricultural features such as hedgerows and grass verges are important for claims verification, environmental management, and regulatory compliance.

Traditionally, these smaller features are assessed through self-reporting, field visits and aerial photography inspections. Larger schemes have adopted automated machine learning approaches such as random forest with object-based image analysis (OBIA).

In this study, 25cm resolution APGB aerial photography and 50cm APGB color infrared (CIR) imagery were used in combination with Picterra's CNN deep learning model to map buffer vegetation features around cropping extents and water resources, focusing on grass verges. Landscape feature height data from APGB's 2m digital surface and 5m terrain models, was added to the optical RGB 25cm data stacks to train additional models and compare classification accuracies.

Models pre-trained on 25cm APGB imagery produced the most reliable results across varied geographies and imagery acquisition dates. The Agency's 1m resolution LiDAR derived Vegetation Object Model (VOM) product, and an NDVI band derived from the

APGB Aerial Photography 50cm colour infrared (CIR) product were also used as ancillary datasets to further test classification accuracies. The VOM dataset provides 1m pixel values representing vegetation height above a threshold of 2.5m.

The digitised training dataset contained just over 7300 ground truth labels. Training samples were selected across 12 areas of interest across the UK with varied geographies, imagery acquisition dates and conditions to strengthen model robustness.

Results showed that 25cm resolution optical data produced the most accurate outcomes with accuracies of over 80% for grass verges, 98.1% for individual trees, and 98.5% for water bodies. Comparative models, trained with and without an auxiliary height band, demonstrated reduced accuracy across all classes when including resampled 2m resolution height data.

Further improvements were achieved by removing more complex urban and built-up areas using the ONS Built-Up Areas 2022 dataset and by incorporating training areas with greater landscape variety and acquisition conditions. This increased the scalability and robustness of the models for application across new datasets.



Figure 3: Classified results for the buffer model trained over APGB 25cm imagery showing grass verge and hedgerow predictions.

Protecting Habitats: Lapwing Nesting Plot Detection

Under a specific scheme, targeted actions relating to specific features and habitats are incentivized, including the creation of lapwing nesting plots within arable land. Lapwings are listed as near threatened on the global IUCN Red List of Threatened Species and classified as red under the UK's Birds of Conservation Concern.

High temporal frequency 3m resolution PlanetScope data, operated by Planet, was assessed in identifying lapwing nesting plots within crop parcels claimed as land use code AB5 under the scheme in 2023. PlanetScope's constellation of 180 CubeSats enables near-daily global acquisitions, increasing the likelihood of multiple cloud-free images each season. Detection areas were limited to within

claimed parcel boundaries to improve prediction accuracy.

Time-series imagery from April, May and July was used to train a deep learning model to predict lapwing plot locations and sizes within AB5 parcels. Results produced using all 8 bands for each month timestamp, 27-bands within a stack, were compared with accuracies using only an NDVI band per month.

Validated nesting plot samples for 2023, provided by the government agency in England, were based on plot commitment sizes and observed vegetation changes over time. These were used to verify nesting site locations for 232 claimed parcels.

April

July

May

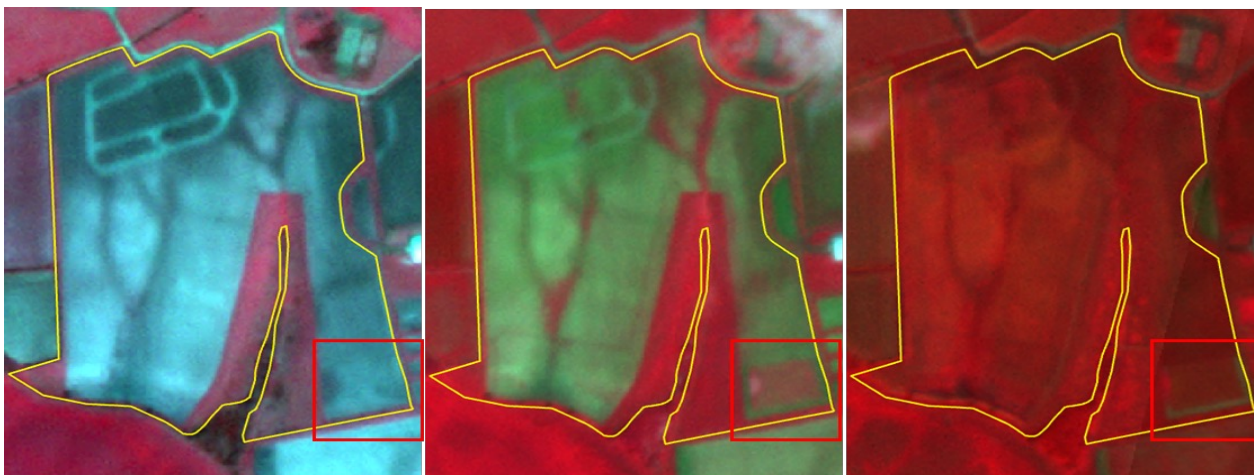


Figure 10: PlanetScope 3m imagery with claimed AB5 parcel boundaries (yellow) and identified 1ha nesting site (red).

Models pre-trained with all 8 PlanetScope bands across the three-monthly acquisitions delivered the highest classification accuracy at 85.5%. Models using only NDVI band per month achieved lower accuracy at 82.5 %.

PlanetScope's 3m imagery proved highly effective in detecting lapwing nesting plots. In 2023, 695 crop parcels were claimed as containing lapwing nesting areas. Of these, 116 were used for model training, with predictions correctly identifying site sizes and locations 85.5% of the time.

For successful habitat creation, lapwing nesting plots should be fallow between March and July with minimal vegetation cover, away from woods or tall hedges and ideally close to wetlands or grazed pasture. The preferred appearance is similar to a rough seedbed or early tillage before mid-March, left undisturbed until mid-July.

The below examples illustrate mapped nesting site areas and locations predicted using the 27-band on untrained novel test sites. Model accuracies decreased for parcels where no nesting site was predicted or where only part of the claimed area was classified.

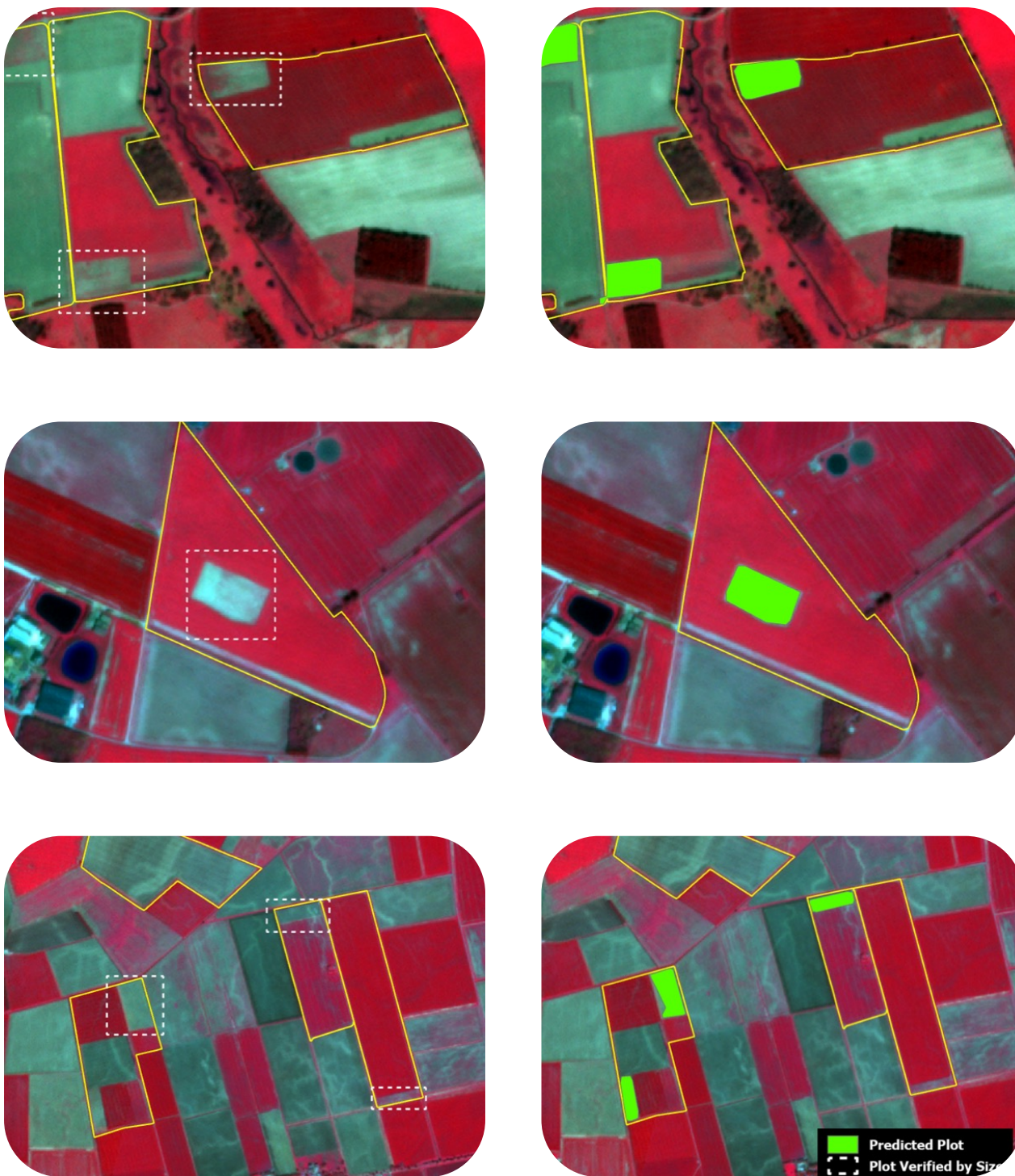


Figure 4: 2023 claimed nesting site parcels verified by commitment size (left) vs 27-band model predictions for plot locations and extents.

Plots with soil and vegetation conditions similar to the 116 training sites were identified most accurately. Sites showing greater contrast with the surrounding cropped area were also more consistently captured, with clearer plot boundaries. Expanding the diversity of training sites would further strengthen model robustness in identifying the full range of conditions used for lapwing plots.

The current nesting site dataset verifies over 80% of claims and flags the remaining cases where in-field or manual checks would be beneficial. Thanks to PlanetScope's high temporal frequency, cloud-free imagery is readily available, supporting scalable national coverage for monitoring these habitats.

Business and Environmental Impact

All three components – Sustainable farming, local habitat, and landscape recovery require large scale planning, management and monitoring by government stakeholder and farmers in order to effectively administer farming subsidies or incentives.

Currently, the Land Parcel Information System (LPIS) maintained by the Agency is updated regularly with information from customers, OS MasterMap, aerial photography and satellite imagery to ensure accurate payment calculations. In addition, a defined percentage of claims must undergo annual control checks. These are conducted either through field inspections or high-resolution Earth observation imagery. Field inspections, however, are costly and impractical for large-scale assessments.

Automated landscape feature mapping offers a more efficient, collaborative approach. It enables comprehensive monitoring of farmland while refining target areas for field visits, allowing inspectors to assess not only cropped parcels but also farming practices and land management. Traditional, Machine learning algorithms such as Random Forest have demonstrated accurate and consistent outputs. However, their reliance on per-image ground truth data for training and validation limits scalability. In contrast, deep learning models can be trained iteratively using historical samples that vary geographically, spectrally, and temporally. This increases model robustness and allows rapid mapping on newly acquired imagery with minimal ground support.

Towards Scalable, Real-Time Landscape Intelligence

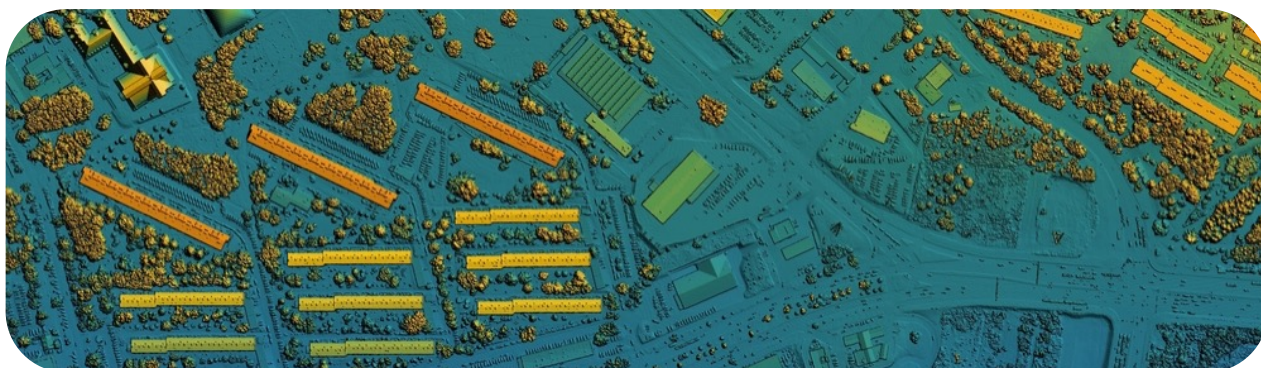
Deep learning models provide significant advantages when applied to Earth observation (EO) imagery. Convolutional Neural Networks (CNNs), in particular, excel at extracting complex patterns in EO data, enabling high performance in land cover classification, feature and object detection, and change monitoring over time.

Through its partnership with AI platform Picterra, Cyient develops robust pre-trained deep learning models that support near real-time landscape mapping and monitoring, delivering scalable, accurate, and actionable insights for environmental and agricultural management.

About the Author



Nicky Squires is a Remote Sensing and Geographic Information Systems Specialist with over nine years' experience in the application of RS and GIS data and methods on projects related to land cover, environmental change, ecosystem services and satellite data evaluation. She has project experience in the UK, South America, Africa and Southeast Asia, working with a wide range of governmental, business and international organizations, including the UK Space Agency, Forestry Commission Scotland and the Department of International Development.



About Cyient

Cyient (Estd: 1991, NSE: CYIENT) delivers intelligent engineering solutions across products, plants, and networks for over 300 global customers, including 30% of the top 100 global innovators. As a company, Cyient is committed to designing a culturally inclusive, socially responsible, and environmentally sustainable tomorrow together with our stakeholders.

For more information, please visit
www.cyient.com



Contact Us

North America Headquarters

Cyient, Inc.
99 East River Drive
5th Floor
East Hartford, CT 06108
USA
T: +1 860 528 5430
F: +1 860 528 5873

Europe, Middle East, and Africa Headquarters

Cyient Europe Limited
Apex, Forbury Road,
Reading
RG1 1AX
UK
T: +44 118 3043720

Asia Pacific Headquarters

Cyient Limited
L14, 333, Collins Street
Melbourne, Victoria, 3000
Australia
T: +61 4 7026 3817
F: +61 3 8601 1180

Global Headquarters

Cyient Limited
Plot No. 11
Software Units Layout
Infocity, Madhapur
Hyderabad - 500081
India
T: +91 40 6764 1000
F: +91 40 2311 0352

Follow us on:  