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A Semi-Analytical Surrogate and Two-Stage Deep Learning Framework for Defect Detection and Sizing in Above-Ground Inspection of Buried Pipelines

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Abstract

Above-ground electromagnetic inspection assesses buried pipelines by injecting a time-harmonic current and measuring the resulting magnetic field. A metal-loss defect redistributes the current, perturbing this microtesla-scale field by a few to ten nanotesla—comparable to the variation from sensor lift-off and lateral offset. This weak, confounded signal motivates learning-based interpretation, which requires datasets far larger than finite-element analysis can affordably supply. A semi-analytical magnetic-flux-density surrogate model is therefore developed that combines an annular skin-effect current solution with a Biot–Savart perturbation over a finite corrosion sector. Validated against the finite-element reference, the surrogate reproduces the defect-induced perturbation trends with errors on the order of 10^{-9} T and a correlation coefficient of 0.986 for a representative case. Using the surrogate, 58,080 multi-frequency inspection cases at 1 Hz and 1000 Hz are generated, each as a four-channel axial scan, and used to train a two-stage pipeline: a convolutional classifier detects the defect, and a defect-only regressor then estimates depth fraction, width, and length. All results are in-distribution, with training and testing data generated from the same surrogate family. On the held-out test set, the classifier achieved 96.05% accuracy, 100.00% precision, and 94.72% recall, and the regressor reached R^2 values of 0.958, 0.923, and 0.835 for depth fraction, width, and length, respectively. These results establish a scalable path from finite-element feasibility to automated defect inference, with experimental validation the remaining step.

Keywords: buried pipelines; above-ground inspection; non-destructive evaluation; skin effect; semi-analytical modeling; deep learning; defect sizing

1 Introduction

Underground pipelines are critical assets for transporting oil, gas, refined products, and other fluids over long distances. Their failure can cause environmental contamination, major financial losses, regulatory penalties, and loss of human life. Maintaining the integrity of buried pipelines is therefore a central problem in non-destructive evaluation (NDE) and infrastructure monitoring [1, 2]. Beyond inspection and defect detection, accurate structural integrity and failure-pressure assessment remain essential for safe pipeline operation, especially when corrosion damage becomes severe [3]. Among the many degradation mechanisms that affect underground lines, corrosion-driven metal loss remains one of the most important because it gradually reduces wall thickness and may evolve unnoticed beneath coatings or in inaccessible regions.

Conventional in-line inspection (ILI) is widely used in industry, but it is not universally applicable. Pig-based systems require launch and receive facilities, favorable internal geometry, and uninterrupted passage through the line. Many pipelines are unpiggable because of diameter changes, tight bends, flow restrictions, missing pigging infrastructure, or operational limitations [1, 2]. These limitations continue to motivate external and above-ground inspection methods that can assess pipeline condition without requiring access from inside the pipe.

External NDE methods investigated for pipeline inspection include guided-wave ultrasonics, magnetic flux leakage, eddy-current methods, and alternating current field measurement. Guided-wave inspection can screen long ranges, but attenuation, coating condition, geometric complexity, and transducer coupling affect the usable range; direct pipe access is generally required [4, 5]. Magnetic particle inspection and magnetic flux leakage

detect flux distortion or particle accumulation associated with metal loss and surface-breaking flaws, but both methods require close access and small lift-off distances [6–8]. Eddy-current methods are constrained by lift-off, penetration depth, and deployment limits in coated or buried steel pipes [9–12]. Alternating current field measurement is effective for near-surface crack inspection, but its conventional operating regime is short stand-off inspection of surface-breaking flaws rather than meter-scale sensing from above ground [13–17]. These access and stand-off requirements leave above-ground inspection of buried pipelines underserved.

Above-ground electromagnetic inspection methods such as NoPig and AGIT inject alternating current into the buried pipe and measure the resulting magnetic field above ground [18, 19]. Metal-loss defects redistribute current in the wall and perturb the external magnetic field. Because the current distribution depends on frequency through the skin effect, measurements at multiple frequencies provide depth contrast: low-frequency excitation samples more of the wall thickness, whereas high-frequency excitation emphasizes the near-surface region. This approach enables inspection from the ground surface without requiring tool passage inside the line and at stand-off distances comparable to typical burial depths [18, 19].

The defect-induced perturbation is weak compared with the baseline magnetic field of the intact pipe. At meter-scale stand-off distances, it is often at the nanotesla or sub-nanotesla level [20]. The measured signal is also sensitive to sensor lift-off and lateral offset, which can introduce variations comparable to or larger than the defect signal itself. Our earlier finite-element-based study established the physical feasibility of the method using detailed ANSYS Electronics Desktop simulations [20]. That work showed that a buried-pipeline defect can perturb the magnetic flux density measured about one meter above the pipe, and that the perturbation depends on defect orientation and excitation frequency. Sensor movement can also introduce deviations comparable to or larger than the defect-induced change [19–22]. Low–high frequency comparison is therefore used as a mechanism for separating frequency-dependent defect signatures from geometry-driven motion artifacts.

Building directly on that foundation, the present study introduces a semi-analytical forward solver, a structured dataset generator, and a two-stage learning framework for automated detection and sizing. The finite-element model remains the physical reference. The semi-analytical model approximates the modeled current-penetration and defect-perturbation mechanisms at lower computational cost than repeated full three-dimensional finite-element simulations, enabling scalable synthetic data generation for learning-based defect interpretation.

The main contributions of this paper are:

- A semi-analytical forward model for multi-frequency above-ground magnetic-field prediction in the presence of localized outer-surface corrosion.
- A comparison between the semi-analytical formulation and the finite-element reference to verify that the defect-centered perturbation shape and frequency-dependent response are retained.
- A large structured dataset generated by the forward solver, spanning defect depth, width, length, circumferential position, and scan radius.
- A two-stage learning framework in which a classifier detects the presence of a defect and a defect-only regressor estimates defect depth fraction, width, and length.

Together, these contributions move the problem from feasibility analysis toward scalable, physics-informed defect inference for above-ground electromagnetic pipeline inspection.

The remainder of the paper is organized as follows. Section 2 presents the theoretical background of multi-frequency above-ground electromagnetic sensing. Section 3 presents the semi-analytical model, the finite-element agreement study, the dataset-generation process, and the two-stage learning framework. Section 4 discusses the results. Section 5 concludes the paper.

2 Theoretical Background: Frequency-Dependent Current Distribution in Cylindrical Conductors and Its External Magnetic Field

The method injects a time-harmonic current into a buried pipeline and measures the magnetic field above ground. This operating principle is consistent with above-ground electromagnetic inspection concepts such as NoPig and AGIT, in which the pipe acts as the current-carrying conductor and corrosion is inferred from perturbations in the external magnetic field [18–20]. For an intact pipe under ideal symmetry, the external magnetic field is primarily circumferential and varies with radial distance from the pipe axis. When metal loss is present, axial current redistributes around the damaged region. The redistribution creates a localized magnetic-field distortion that can be sensed above ground.

Current distribution within a conductor depends on AC frequency. The characteristic depth to which the current penetrates is the skin depth,

$$\delta = \sqrt{\frac{2}{\omega\mu\sigma}} = \frac{1}{\sqrt{\pi\mu\sigma f}}, \quad (1)$$

where δ is the skin depth, $\omega = 2\pi f$ is the angular frequency, f is the excitation frequency, μ is the effective magnetic permeability used in the skin-depth estimate, and σ is the electrical conductivity [23]. Because δ varies inversely with $\sqrt{f}$, changing the excitation frequency changes the portion of the wall sampled by the injected current. Low-frequency current penetrates more of the wall thickness and is sensitive to volumetric metal loss. High-frequency current is confined closer to the outer surface and is sensitive to surface-breaking corrosion.

The external magnetic field reflects this depth-dependent current distribution. Comparing measurements across frequencies separates defect signatures, which change with current penetration, from sensor-position artifacts such as lift-off and lateral offset, which primarily change with measurement geometry. Multi-frequency scanning therefore provides complementary depth information from one scan and reduces dependence on a single-frequency threshold.

In this work, two excitation frequencies are considered: 1 Hz and 1000 Hz. At 1 Hz, the current penetrates more deeply into the pipe wall, increasing interaction with the defect volume. At 1000 Hz, the current is concentrated closer to the outer region of the wall, changing the perturbation pattern produced by an outer-surface defect. The contrast between these regimes is used for distinguishing intact and defected cases and for characterizing defect severity. Current-density distributions for the two regimes are given in Fig. 1.

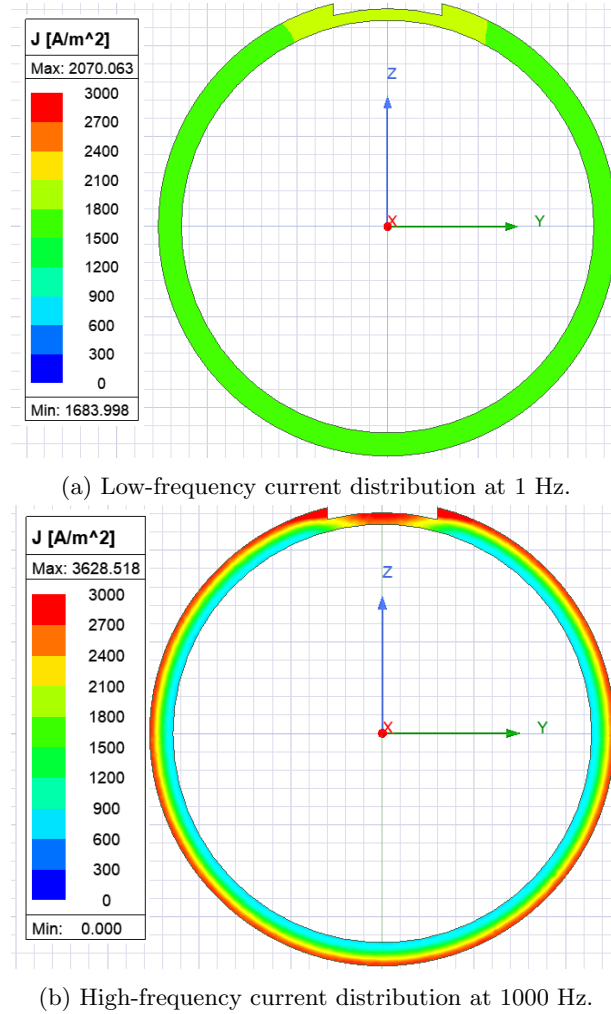


Figure 1: Low- and high-frequency current-density patterns in a defected pipe. The 1 Hz case penetrates more of the wall; the 1000 Hz case is concentrated near the outer surface.

The magnetic flux density is evaluated using two components: the tangential component $B_t \equiv B_\theta$ and the normal component $B_n \equiv B_r$. Here, “normal” refers to the radial direction with respect to the pipe axis, not necessarily the vertical direction relative to the ground surface. The tangential component is associated with the circumferential baseline field and its local distortion. The normal component reflects symmetry breaking and radial leakage associated with current deflection around the defect. In the earlier finite-element study, tangential perturbations were more pronounced for defects near the top or bottom of the pipe cross-section, whereas the normal component was particularly informative for side-oriented defects [20]. Using both components therefore improves sensitivity to defect location and geometry.

The model used in this study includes three mechanisms: frequency-dependent skin-effect penetration, current redistribution caused by localized metal loss, and different tangential and normal field responses to that redis-

tribution. These mechanisms provide the physical basis for using multi-frequency, multi-component magnetic sensing in above-ground inspection of buried pipelines.

3 Methodology

A physics-informed simulation-to-learning pipeline is used for above-ground electromagnetic pipeline inspection. The semi-analytical forward model predicts the multi-frequency magnetic field of an intact or defected buried pipe using the skin-effect current solution and the perturbation from a localized wall-loss defect. The model then generates a structured dataset spanning defect geometry, circumferential position, and scan radius. Radius-conditioned additive Gaussian noise with a 1%–5% amplitude scale is added to approximate measurement variability and to avoid training on noise-free signatures. The dataset trains a two-stage pipeline: a classifier detects the defect, and a defect-only regressor sizes it. The pipeline links electromagnetic physics, scalable data generation, and automated detection and sizing.

3.1 Physics-based forward modeling and dataset generation

Physics-based forward modeling proceeds in two stages. First, a semi-analytical model computes the magnetic field for a specified pipe, scan, and defect geometry. Second, the model is evaluated across a parameter sweep to generate the dataset. These two stages convert the electromagnetic model into the multi-frequency signatures used for learning-based detection and sizing. Section 3.1.1 develops the model, and Section 3.1.3 describes the parameter sweep.

3.1.1 Semi-analytical magnetic-flux-density model

A semi-analytical magnetic-flux-density model is developed for a long hollow conducting pipe with an outer-surface corrosion defect. The model combines an analytical skin-effect current solution in the pipe wall with a Biot–Savart perturbation for the field distortion from a finite defect sector. It retains the frequency-dependent penetration and local defect-perturbation mechanisms used by the learning dataset. Its cost is lower than full three-dimensional finite-element analysis because each evaluation uses an annular closed-form current solution and reduced numerical quadrature rather than a full three-dimensional mesh solve [20, 24–27]. The surrounding medium is approximated as nonconductive and nonmagnetic. Soil, coating, and air–soil-interface effects are therefore not modeled here.

All quantities are treated as phasors under the time-harmonic convention

$$\Re\{\cdot e^{i\omega t}\}, \quad \omega = 2\pi f.$$

The semi-analytical solver computes complex magnetic-field phasors. Either the real part or the magnitude may be retained as the measurement output. In the present dataset, the real part is used.

The pipe is modeled as a hollow cylindrical conductor with outer radius a , wall thickness t , and inner radius

$$b = a - t.$$

An outer-surface corrosion defect is represented by a finite circumferential sector of axial length ℓ , depth d , and arc-length width w . The circumferential span is

$$\Delta\theta = \frac{w}{a}, \tag{2}$$

and the defect occupies

$$\theta \in [\theta_1, \theta_2], \quad z \in [-\ell/2, \ell/2], \quad \theta_2 - \theta_1 = \Delta\theta.$$

The defect center angle is

$$\theta_c = \frac{\theta_1 + \theta_2}{2}.$$

Within the defect sector, the outer radius is reduced to

$$a_d = a - d.$$

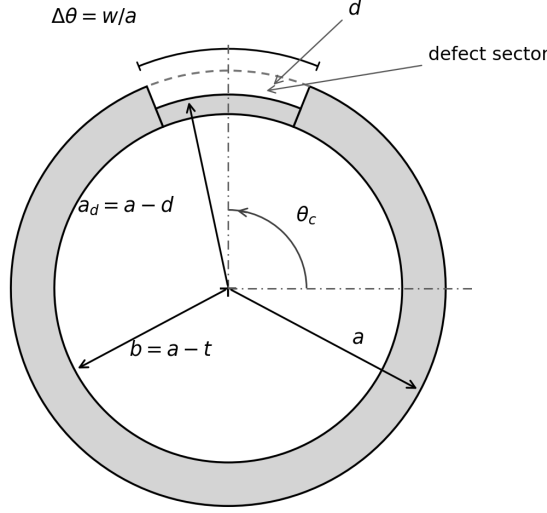


Figure 2: Cross-section of the outer-surface corrosion sector used in the semi-analytical model. The defect has center angle θ_c , depth d , circumferential span $\Delta\theta = w/a$, and reduced outer radius $a_d = a - d$.

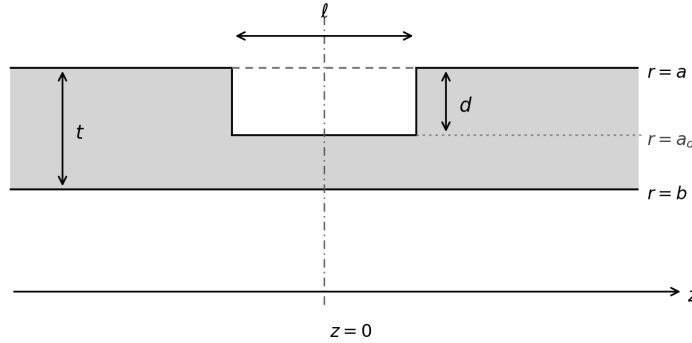


Figure 3: Axial section through the defect center. The defect has axial length ℓ and depth d below the outer surface $r = a$, over the reduced wall $r = a_d$.

Governing equations and field reduction

In the conducting pipe wall, the electromagnetic response is modeled under the magnetoquasistatic approximation. This approximation neglects displacement current relative to conduction current, i.e., $\sigma \gg \omega\epsilon$, which is appropriate for conductive steel at the low excitation frequencies considered here. For a linear, isotropic, and locally homogeneous conductor, Maxwell's equations and Ohm's law are written as [24–26]

$$\nabla \times \mathbf{H} = \mathbf{J}, \quad \mathbf{J} = \sigma \mathbf{E}, \quad \mathbf{B} = \mu \mathbf{H}, \quad \nabla \times \mathbf{E} = -i\omega \mathbf{B}, \quad (3)$$

with $\nabla \cdot \mathbf{B} = 0$. Eliminating $\mathbf{E}$ and $\mathbf{J}$ yields a second-order governing equation for the magnetic field. Taking the curl of Ampère's law gives

$$\nabla \times (\nabla \times \mathbf{H}) = \nabla \times \mathbf{J} = \nabla \times (\sigma \mathbf{E}). \quad (4)$$

For a locally homogeneous conductor with spatially uniform conductivity, $\nabla \sigma = 0$, so that

$$\nabla \times (\nabla \times \mathbf{H}) = \nabla \times \mathbf{J} = \sigma \nabla \times \mathbf{E} = -i\omega \mu \sigma \mathbf{H}. \quad (5)$$

In regions of uniform permeability, $\nabla \cdot \mathbf{H} = 0$, so that the vector identity

$$\nabla \times (\nabla \times \mathbf{H}) = \nabla(\nabla \cdot \mathbf{H}) - \nabla^2 \mathbf{H}$$

reduces the governing equation to

$$\nabla^2 \mathbf{H} = i\omega\mu\sigma \mathbf{H}. \quad (6)$$

Equation (6) is a complex diffusion, or Helmholtz-type, equation for the magnetic field in the conducting wall. With the phasor convention $\exp(i\omega t)$, the coefficient appears as $+i\omega\mu\sigma$. To express the annular radial equation in ordinary-Bessel form, we define the complex radial wavenumber

$$q^2 = -i\omega\mu\sigma, \quad q = \sqrt{-i\omega\mu\sigma}. \quad (7)$$

For positive real μ and σ , the branch is chosen as

$$q = (1 - i)\sqrt{\frac{\omega\mu\sigma}{2}}, \quad (8)$$

so that the radial solution represents skin-effect attenuation rather than exponential growth away from the conducting surface. Equivalently, if $\gamma^2 = i\omega\mu\sigma$ is used, then $\gamma = (1 + i)/\delta$, where $\delta = \sqrt{2/(\omega\mu\sigma)}$, and $q = -i\gamma$. The present paper uses the ordinary-Bessel representation with q consistently.

Annular skin-effect solution for the intact pipe

For a long pipe carrying a net axial current under the axisymmetric approximation, the modeled magnetic field in the conductor is azimuthal and the current density is axial, so that

$$\mathbf{H} = \hat{\boldsymbol{\theta}} H_\theta(r), \quad \mathbf{J} = \hat{\mathbf{z}} J_z(r).$$

Substituting $\mathbf{H} = \hat{\boldsymbol{\theta}} H_\theta(r)$ into (6) requires the azimuthal component of the vector Laplacian,

$$(\nabla^2 \mathbf{H})_\theta = \frac{d^2 H_\theta}{dr^2} + \frac{1}{r} \frac{dH_\theta}{dr} - \frac{H_\theta}{r^2}.$$

Using $q^2 = -i\omega\mu\sigma$ then yields the ordinary Bessel equation of order one [24, 25, 28, 29]

$$\frac{d^2 H_\theta}{dr^2} + \frac{1}{r} \frac{dH_\theta}{dr} + \left(q^2 - \frac{1}{r^2}\right) H_\theta = 0, \quad b < r < a. \quad (9)$$

Its general solution in the annular conductor is

$$H_\theta(r) = A J_1(qr) + B Y_1(qr), \quad (10)$$

where $J_n(\cdot)$ and $Y_n(\cdot)$ denote Bessel functions of the first and second kind, respectively. This form is mathematically equivalent to a modified-Bessel representation with a rotated complex argument; the present notation is chosen to remain consistent with ordinary-Bessel tubular-conductor formulations.

The corresponding axial current density follows from Ampère's law in cylindrical coordinates,

$$(\nabla \times \mathbf{H})_z = \frac{1}{r} \frac{d}{dr} (r H_\theta(r)) = J_z(r). \quad (11)$$

Using the Bessel-function identities

$$\frac{1}{r} \frac{d}{dr} [r J_1(qr)] = q J_0(qr), \quad \frac{1}{r} \frac{d}{dr} [r Y_1(qr)] = q Y_0(qr),$$

gives

$$J_z(r) = q [A J_0(qr) + B Y_0(qr)]. \quad (12)$$

Equations (10) and (12) form the radial backbone of the semi-analytical forward solver. Once the coefficients (A, B) are known, the intact current-density profile can be evaluated on a radial grid for any excitation frequency.

The coefficients are determined from the physically motivated boundary conditions

$$H_\theta(b) = 0, \quad H_\theta(a) = \frac{I}{2\pi a}, \quad (13)$$

where I is the net axial current. The inner condition reflects the idealized hollow-core assumption: for $r < b$ there is no enclosed current, so the circumferential magnetic field vanishes under infinite-pipe symmetry. The outer condition follows from Ampère's law evaluated immediately outside the conductor. Substituting (10) into (13) yields

$$\begin{bmatrix} J_1(qb) & Y_1(qb) \\ J_1(qa) & Y_1(qa) \end{bmatrix} \begin{bmatrix} A \\ B \end{bmatrix} = \begin{bmatrix} 0 \\ I/(2\pi a) \end{bmatrix}.$$

Defining

$$D = J_1(qa)Y_1(qb) - J_1(qb)Y_1(qa),$$

the closed-form solution is

$$A = \frac{I}{2\pi a} \frac{Y_1(qb)}{D}, \quad B = -\frac{I}{2\pi a} \frac{J_1(qb)}{D}. \quad (14)$$

In implementation, the equivalent matrix form is used for numerical robustness across frequencies and material parameters.

Defect sector and current-redistribution surrogate

A full solution of the three-dimensional current-redistribution problem around a local wall-loss defect would remove the computational advantage of the semi-analytical formulation. Accordingly, a sector-current surrogate is introduced. Under intact circumferential symmetry, the fraction of the total axial current associated with an angular sector of width $\Delta\theta$ is proportional to its angular span. The nominal sector current is therefore defined as

$$I_{\text{sector}} = I \frac{\Delta\theta}{2\pi}. \quad (15)$$

This quantity should be interpreted as the intact-pipe current fraction used to construct the local defect surrogate, not as an exact current-conservation condition for the fully three-dimensional defected pipe. Using this sector current, two radial current-density profiles are constructed:

- the baseline sector current density $J_{\text{base}}(r)$, computed from (12) on the intact annulus $b < r < a$ with $(a, b, I_{\text{sector}})$;
- the defect-sector current density $J_{\text{act}}(r)$, computed from (12) on the reduced annulus $b < r < a_d$ with $(a_d, b, I_{\text{sector}})$, and set to zero for $r > a_d$.

The equivalent perturbation current density is then defined by

$$J_{\text{diff}}(r) = J_{\text{act}}(r) - J_{\text{base}}(r). \quad (16)$$

The difference-current representation acts as a surrogate for defect-induced axial-current redistribution. It is nonzero only in the defect-sector volume and therefore serves naturally as the source term for the perturbation magnetic field. It should be interpreted as an equivalent perturbation source rather than a fully self-consistent three-dimensional current solution; local radial and circumferential closure currents near the axial and angular defect boundaries are not explicitly resolved.

Biot–Savart integral and analytic axial reduction

The total magnetic field is written as the superposition of the full intact-pipe baseline and the defect-induced perturbation:

$$\mathbf{B}_{\text{total}}(\mathbf{r}) = \mathbf{B}_0(\mathbf{r}) + \Delta\mathbf{B}_{\text{defect}}(\mathbf{r}). \quad (17)$$

Here, $\mathbf{B}_0$ denotes the magnetic field of the complete intact pipe carrying the total current I . The perturbation term $\Delta\mathbf{B}_{\text{defect}}$ is computed only from the equivalent difference current J_{diff} defined in the defect-sector volume. Thus, the sector contribution is not added twice: the baseline field represents the intact full pipe, while the perturbation replaces the local intact-sector current by the reduced-wall defect-sector current under the assumption that the non-defect sectors remain unchanged. For the intact pipe, the external baseline field is approximated by the classical circumferential field outside a long straight current-carrying cylinder. For an observation radius $R > a$ in the surrounding nonconductive and nonmagnetic medium, Ampère’s law gives

$$B_{\theta,0}(R) = \mu_0 \frac{I}{2\pi R}, \quad B_{r,0} = 0. \quad (18)$$

Here, R is the radial distance from the pipe axis to the observation point. This expression assumes an axisymmetric intact current distribution, an effectively long pipe, and a surrounding medium with permeability μ_0 . Thus, finite-length end effects, current-return-path effects, soil or coating electromagnetic properties, and magnetization-boundary perturbations are not included in the intact baseline. These effects are treated as outside the fidelity of the present semi-analytical approximation and are assessed indirectly through comparison with the finite-element reference [20, 24, 27]. The defect contribution is then computed from the Biot–Savart law for an equivalent volume current source in the surrounding medium [24, 27]:

$$\Delta\mathbf{B}(\mathbf{r}) = \frac{\mu_0}{4\pi} \iiint_{V_{\text{defect}}} \frac{\mathbf{J}_{\text{diff}}(\mathbf{r}') \times (\mathbf{r} - \mathbf{r}')}{\|\mathbf{r} - \mathbf{r}'\|^3} dV'. \quad (19)$$

where the equivalent current density is

$$\mathbf{J}_{\text{diff}}(\mathbf{r}') = J_{\text{diff}}(r') \hat{\mathbf{z}},$$

the defect-sector volume element is

$$dV' = r' dr' d\theta' dz',$$

and the integration limits are

$$r' \in [b, a], \quad \theta' \in [\theta_1, \theta_2], \quad z' \in [-\ell/2, \ell/2].$$

Here, the free-space permeability μ_0 is used for the surrounding medium. Permeability-boundary and magnetization effects associated with the ferromagnetic pipe are therefore represented approximately through the equivalent-current perturbation and are assessed through comparison with the finite-element reference.

Let the observation point be $\mathbf{r} = (x_o, y_o, z)$ and the source point be $\mathbf{r}' = (x', y', z')$, and define

$$\rho^2 = (x_o - x')^2 + (y_o - y')^2.$$

Then

$$\|\mathbf{r} - \mathbf{r}'\|^2 = \rho^2 + (z - z')^2.$$

Because the dependence on z' is isolated in the factor $\rho^2 + (z - z')^2$, the axial integral can be evaluated analytically. Let

$$u = z - z', \quad du = -dz'.$$

Then the integration limits transform as $z' = -\ell/2 \mapsto u = z + \ell/2$ and $z' = \ell/2 \mapsto u = z - \ell/2$. Therefore,

$$\int_{-\ell/2}^{\ell/2} \frac{dz'}{(\rho^2 + (z - z')^2)^{3/2}} = \int_{z-\ell/2}^{z+\ell/2} \frac{du}{(\rho^2 + u^2)^{3/2}} = \left[\frac{u}{\rho^2 \sqrt{\rho^2 + u^2}} \right]_{u=z-\ell/2}^{u=z+\ell/2}. \quad (20)$$

The analytic axial integration reduces the original three-dimensional Biot-Savart integral to a two-dimensional numerical quadrature over the defect cross-sectional sector. The reduction preserves the finite axial-length effect while lowering the numerical cost relative to direct three-dimensional volume integration.

Numerical quadrature, measurement extraction, and stability

After the analytic reduction (20), the remaining integrals over (r', θ') are evaluated numerically using trapezoidal quadrature on uniform grids:

$$r'_i = b + \frac{i-1}{N_r-1}(a-b), \quad \theta'_j = \theta_1 + \frac{j-1}{N_\theta-1}(\theta_2 - \theta_1).$$

For each scan point z_k , the model computes the Cartesian perturbation field components (B_x, B_y) and then projects them onto the radial and tangential directions associated with the scan-line azimuth ϕ_{line} . Here, ϕ_{line} is defined as the azimuthal angle of the scan-line position vector in the cross-sectional (x, y) plane, measured counterclockwise from the positive x -axis. Thus, the observation location in the cross-section is

$$x_o = R_{\text{line}} \cos \phi_{\text{line}}, \quad y_o = R_{\text{line}} \sin \phi_{\text{line}}.$$

The corresponding radial and tangential unit vectors are

$$\hat{\mathbf{r}} = \cos \phi_{\text{line}} \hat{\mathbf{x}} + \sin \phi_{\text{line}} \hat{\mathbf{y}}, \quad \hat{\boldsymbol{\theta}} = -\sin \phi_{\text{line}} \hat{\mathbf{x}} + \cos \phi_{\text{line}} \hat{\mathbf{y}}.$$

Therefore, the component projection is

$$B_r = B_x \cos \phi_{\text{line}} + B_y \sin \phi_{\text{line}}, \quad B_\theta = -B_x \sin \phi_{\text{line}} + B_y \cos \phi_{\text{line}}. \quad (21)$$

The projected quantities B_r and B_θ are interpreted as the normal and tangential magnetic-flux-density components measured in the above-ground scan. Repeating this procedure at each excitation frequency produces the four-channel signature used throughout the paper:

$$\left[B_t^{(1)}, B_n^{(1)}, B_t^{(1000)}, B_n^{(1000)} \right].$$

The dataset generator stores either the real part of the phasor or its magnitude as a user option. In the present dataset, the real part is used.

Overall, the semi-analytical model combines an annular skin-effect solution with a finite-defect perturbation integral. It retains the mechanisms established in the earlier finite-element-based study—frequency-dependent current penetration, defect-induced current redistribution, and directional magnetic-field perturbation—while reducing the data-generation cost relative to repeated full three-dimensional finite-element simulations [20].

3.1.2 Agreement with finite-element simulations

The finite-element model remains the high-fidelity reference and follows the ANSYS-based setup established in the earlier study [20]. The pipe section is 2 m long, with outer diameter 10 in (254 mm) and wall thickness 0.5 in (12.7 mm), and it carries a sinusoidal 16 A excitation at 1 Hz. Although the semi-analytical formulation assumes an axially long pipe, the finite-element scan region is centered near the middle of the pipe to reduce end effects. For the single defected validation case below, the magnetic field is evaluated along an axial scan line from $z = -0.5$ m to $z = 0.5$ m, where $z = 0$ corresponds to the defect center. The sensor is positioned 0.5 m above the outer surface of the pipe. The defect is an outer-surface rectangular metal-loss region of length 6 cm, width 6 cm, and depth equal to 50% of the wall thickness.

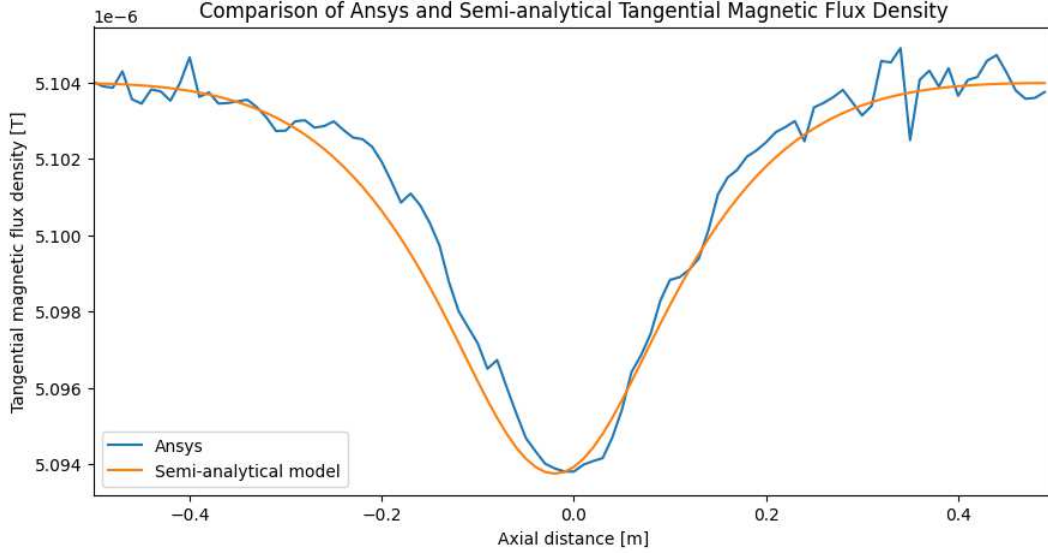


Figure 4: ANSYS and semi-analytical tangential magnetic flux density for a single defected validation case at 1 Hz excitation. The scan line spans $z = -0.5$ m to $z = 0.5$ m at the 12 o'clock position, 0.5 m above the pipe surface.

Shown in Fig. 4 is the agreement between the semi-analytical model and the finite-element reference for the single defected validation case. The semi-analytical profile captures the defect-centered reduction in tangential magnetic flux density, the location of the minimum near the defect center, and the recovery toward the baseline away from the defected region. Error metrics were computed directly from the ANSYS and semi-analytical curve data. The mean absolute error is 5.38×10^{-10} T (0.54 nT), the root-mean-square error is 6.88×10^{-10} T (0.69 nT), and the maximum absolute pointwise error is 1.70×10^{-9} T (1.70 nT). The correlation coefficient between the two curves is 0.986, and the coefficient of determination is $R^2 = 0.958$. The relative error in the peak tangential magnetic flux density is about 0.024%. These metrics quantify agreement in both profile shape and amplitude while avoiding a full three-dimensional finite-element solve for each synthetic-data case.

Across the broader agreement study, the mean absolute error between the semi-analytical and finite-element curves is on the order of 10^{-9} T, the correlation coefficient is 0.94, and the percentage absolute error at the center point directly above the defect is approximately 0.5%. For intact pipes, the model reproduces the expected external tangential baseline and negligible normal component. For defected pipes, it reproduces the location and shape of the perturbation around the defect center and captures the frequency-dependent change in perturbation associated with increasingly surface-confined current flow. These broader-study metrics complement the single-profile metrics reported for Fig. 4.

For nearly overlapping curves of this type, absolute error measures such as MAE and RMSE are often more informative than a single goodness-of-fit coefficient. The reason is that R^2 can be sensitive to very small local deviations when the overall signal variation is narrow compared with the absolute field baseline. The profile-level and broader-study metrics support the use of the semi-analytical model as a lower-cost approximation to full finite-element analysis for synthetic data generation.

3.1.3 Dataset generation

The semi-analytical model is used to generate a long-format CSV dataset in which each case has one identifier and exactly 11 rows, corresponding to 11 axial scan locations:

$$z = -0.5, -0.4, \dots, 0.4, 0.5 \text{ m.}$$

At each location, the following four channels are stored:

$$\left[B_t^{(1)}, B_n^{(1)}, B_t^{(1000)}, B_n^{(1000)} \right].$$

Additional columns store the class label, defect depth fraction, defect length, defect width, defect center angle, and scan radius.

The parameter sweep spans:

- defect depth fraction:

$$d_{\text{frac}} \in \{0.0, 0.1, \dots, 0.9\},$$

- defect length:

$$\ell \in \{0, 10, 20, \dots, 100\} \text{ mm},$$

- defect width:

$$w \in \{0, 10, 20, \dots, 100\} \text{ mm},$$

- defect center angle:

$$\theta_c \in \{0^\circ, 45^\circ, \dots, 315^\circ\},$$

- scan radius:

$$R_{\text{line}} \in \{a + 0.5, a + 0.6, \dots, a + 1.0\} \text{ m}.$$

The parameter sweep produces

$$10 \times 11 \times 11 \times 8 \times 6 = 58,080$$

cases and

$$58,080 \times 11 = 638,880$$

rows.

To approximate measurement variability and prevent training on noise-free signatures, additive white Gaussian noise is introduced into the magnetic-field channels during dataset generation. The noise is radius conditioned because the signal amplitude depends on scan radius. A single global noise level would not reflect the channel scale at different stand-off distances. To avoid conflict with the cylindrical radial coordinate r , the radius-group index is denoted by g . For channel c and scan-radius group g , a representative channel amplitude is defined as

$$A_{c,g} = \frac{1}{N_{c,g}} \sum_{n=1}^{N_{c,g}} \left| x_{c,g}^{(n)} \right|, \quad (22)$$

where $x_{c,g}^{(n)}$ denotes the clean channel value from the n th sample belonging to the same radius group and $N_{c,g}$ is the number of such samples. The noisy channel is then written as

$$\tilde{x}_{c,g} = x_{c,g} + \epsilon_{c,g}, \quad \epsilon_{c,g} \sim \mathcal{N}(0, \nu_{c,g}^2), \quad (23)$$

with noise standard deviation

$$\nu_{c,g} = \alpha_{c,g} A_{c,g}, \quad \alpha_{c,g} \sim \mathcal{U}(0.01, 0.05). \quad (24)$$

The factor $\alpha_{c,g}$ is drawn independently for each channel-radius-group pair and sets the standard deviation for that pair. The noise standard deviation is therefore between 1% and 5% of the mean absolute value of the same channel at the same scan radius. This range is a first-order engineering approximation for sensor noise, lift-off variation, lateral positioning, digitization, and environmental interference; it is not a sensor-calibrated noise model.

The perturbation level remains proportional to the channel magnitude at the same stand-off condition. The added noise reduces overfitting to idealized signatures while preserving the modeled defect-related structure. The mean absolute channel value is used rather than the signed mean to avoid artificially vanishing noise levels in channels whose positive and negative values partially cancel. Future experimental data can replace this approximation with measured sensor-noise and positioning-error statistics.

If any of $(d_{\text{frac}}, \ell, w)$ is zero, the generator forces all three to zero and also runs the forward model with no defect. Thus the class label is physically consistent:

$$\text{class} = \begin{cases} 0, & \text{if any of } d_{\text{frac}}, \ell, w \text{ is zero,} \\ 1, & \text{otherwise.} \end{cases} \quad (25)$$

The zeroing rule ensures that intact labels correspond to intact simulations.

3.2 Two-stage learning framework

Each inspection case is represented as a grouped sample

$$\mathbf{x} \in \mathbb{R}^{11 \times 4},$$

where the 11 rows correspond to the axial scan positions and the four columns correspond to the measured magnetic-field channels

$$\left[B_t^{(1)}, B_n^{(1)}, B_t^{(1000)}, B_n^{(1000)} \right].$$

Only these four signal channels are used as model inputs. Defect angle and scan radius are retained only as metadata for post hoc analysis and visualization. They are not used by either neural network during training or inference. The grouped samples are split at the sample level into 70% training, 15% validation, and 15% testing subsets. Feature normalization is fitted on the training set only. For the Conv1D classifier implementation, each 11×4 sample is transposed to channel-first form 4×11 .

A two-stage learning strategy is adopted. Stage 1 is a binary classifier that predicts defect versus no-defect. Stage 2 is a defect-only regressor trained only on samples with class label 1, and it predicts defect depth fraction, width, and length. The two-stage decomposition improves interpretability. It also allows the classifier and regressor to specialize in detection and sizing, respectively. The choice of architectures is guided by the structure of the measurement itself rather than by arbitrary model selection. Each sample is a short axial scan composed of 11 ordered positions. The classification task depends on recognizing localized spatial signatures such as defect-centered peaks, dips, and asymmetries that extend over neighboring axial positions and appear jointly across the low- and high-frequency channels. A one-dimensional convolutional network is therefore a natural choice for classification because it extracts local axial patterns with shared filters while remaining insensitive to the exact index at which a similar signature appears. In contrast, once a sample is known to contain a defect, the regression task becomes a fixed-length nonlinear mapping from the complete four-channel response vector to three global geometric quantities. For this stage, a multilayer perceptron is sufficient because the input dimension is small, all 44 features can be presented simultaneously, and the target parameters depend primarily on their joint amplitudes and interactions rather than on deeper hierarchical spatial structure.

3.2.1 Classifier

The classifier uses a 1D convolutional encoder with residual-style blocks, followed by global mean and max pooling and a fully connected head. The Stage 1 input is an ordered axial profile with 11 scan positions and four magnetic-field channels. Neighboring scan points are physically related because they describe how the tangential and normal magnetic components change as the sensor passes over a possible defect. Localized corrosion produces axial dips, peaks, and asymmetries that extend over adjacent scan positions rather than appearing as isolated single-point changes. The Conv1D encoder therefore extracts local axial patterns with shared filters across the scan direction, while the global mean and max pooling summarize the strongest and average defect-sensitive responses over the full profile. The residual blocks allow multiple convolutional layers to be stacked while maintaining stable optimization. Let the classifier output logit be denoted by $s(\mathbf{x})$. The corresponding defect probability is

$$p(\mathbf{x}) = \text{sigmoid}(s(\mathbf{x})) = \frac{1}{1 + e^{-s(\mathbf{x})}}. \quad (26)$$

A predicted defect label is then obtained as

$$\hat{y} = \begin{cases} 1, & p(\mathbf{x}) \geq \tau, \\ 0, & p(\mathbf{x}) < \tau, \end{cases} \quad (27)$$

where the decision threshold is set to $\tau = 0.5$, the neutral operating point of a sigmoid binary classifier (equivalently, the logit condition $s(\mathbf{x}) \geq 0$). This fixed threshold avoids introducing an additional validation-tuned operating parameter and provides a simple, reproducible decision rule.

The classifier is trained using weighted binary cross-entropy with logits. Defining $p_i = \text{sigmoid}(s_i)$, the loss is

$$\mathcal{L}_{\text{cls}} = -\frac{1}{N} \sum_{i=1}^N [\lambda_+ y_i \log p_i + (1 - y_i) \log (1 - p_i)], \quad (28)$$

where $y_i \in \{0, 1\}$ is the true class label and λ_+ is the positive-class weight. In the implementation, this weight is computed from the training split as

$$\lambda_+ = \frac{N_-}{N_+},$$

where N_- and N_+ are the numbers of intact and defected training samples, respectively. This is the standard positive-class weighting form used in binary cross-entropy with logits. Because the present parameter sweep

contains more defected samples than intact samples, $\lambda_+ < 1$; therefore, each positive sample is down-weighted so that the aggregate positive-class contribution is better balanced with the intact-class contribution during optimization.

Stage	Operation	Parameters	Output shape
Input	—	4 channels, 11 points	4×11
Block 1	Residual Conv1D block	$4 \rightarrow 32, k = 3$	32×11
Block 2	Residual Conv1D block	$32 \rightarrow 64, k = 3$	64×11
Block 3	Residual Conv1D block	$64 \rightarrow 128, k = 3$	128×11
Pooling	global mean + global max	concatenated	256
FC-1	Linear + ReLU + Dropout	$256 \rightarrow 256$	256
FC-2	Linear + ReLU + Dropout	$256 \rightarrow 64$	64
Output	Linear	$64 \rightarrow 1$	1

Table 1: Implemented binary classifier used in Stage 1.

The classifier is optimized using AdamW with learning rate 5×10^{-4} and weight decay 10^{-4} . Dropout is 0.10, gradient clipping is applied with maximum norm 1.0, and early stopping is used based on validation loss. Both the classifier and the defect-only regressor are implemented in PyTorch and trained with mini-batch gradient descent.

3.2.2 Defect-only regressor

The regressor receives the same 11×4 signal, but flattened to 44 features and passed through residual multilayer perceptron blocks. After the classification stage has isolated defected cases, the regression problem no longer centers on deciding whether a localized feature exists. Instead, it requires combining the full set of measured amplitudes and profile values into three continuous defect parameters. Because the input is short and fixed in length, flattening does not discard information, and an MLP can directly learn nonlinear couplings among all axial positions, frequencies, and field components at once. This is sufficient for the present problem because the desired outputs, depth fraction, width, and length, are global properties of the defected response rather than spatial maps that require translation equivariance or long-sequence modeling. The residual MLP blocks increase expressive power while keeping the model compact relative to more elaborate sequence architectures. It is trained only on defect samples, so the regression target is

$$\mathbf{y} = [d_{\text{frac}}, w, \ell], \quad (29)$$

and the predicted output is

$$\hat{\mathbf{y}} = [\hat{d}_{\text{frac}}, \hat{w}, \hat{\ell}]. \quad (30)$$

Before training, the regression targets are normalized using training-set statistics:

$$\tilde{\mathbf{y}} = (\mathbf{y} - \mathbf{m}_y) \oslash \mathbf{s}_y. \quad (31)$$

Here, $\mathbf{m}_y$ is the target mean vector, $\mathbf{s}_y$ is the target standard-deviation vector, and $\oslash$ denotes component-wise division. The model predicts normalized targets, and the outputs are mapped back to physical units for evaluation.

The regression loss is a weighted Huber loss. For each target component j , the Huber penalty is

$$\ell_\delta(e_j) = \begin{cases} \frac{1}{2}e_j^2, & |e_j| \leq \delta, \\ \delta(|e_j| - \frac{1}{2}\delta), & |e_j| > \delta, \end{cases} \quad (32)$$

where $e_j = \hat{y}_j - \tilde{y}_j$ is the error in normalized target space. The full weighted loss is

$$\mathcal{L}_{\text{reg}} = \frac{1}{3N} \sum_{i=1}^N \sum_{j=1}^3 \lambda_j \ell_\delta(\hat{y}_{ij} - \tilde{y}_{ij}). \quad (33)$$

The loss is computed in normalized target space using the training-set statistics in the target normalization above. The inverse transformation back to physical units is applied only for reporting MAE, RMSE, and R^2 during evaluation. The target weights are

$$[\lambda_1, \lambda_2, \lambda_3] = [1.5, 1.0, 1.0]$$

and the Huber parameter is

$$\delta = 0.20.$$

The larger weight on depth fraction reflects its observed sensitivity to magnetic-perturbation amplitude in the generated data.

Stage	Operation	Parameters	Output shape
Input	flatten	$11 \times 4 \rightarrow 44$	44
FC-in	Linear + ReLU + Dropout	$44 \rightarrow 256$	256
Res block 1	MLP residual block	$256 \rightarrow 256 \rightarrow 256$	256
Res block 2	MLP residual block	$256 \rightarrow 256 \rightarrow 256$	256
FC-out	Linear + ReLU + Dropout	$256 \rightarrow 128$	128
Output	Linear	$128 \rightarrow 3$	3

Table 2: Implemented defect-only regressor used in Stage 2.

The regressor is optimized using AdamW with learning rate 10^{-3} and weight decay 10^{-4} . As in the classifier, dropout is 0.10, gradient clipping is applied, and early stopping is used based on validation loss.

3.2.3 Inference and evaluation

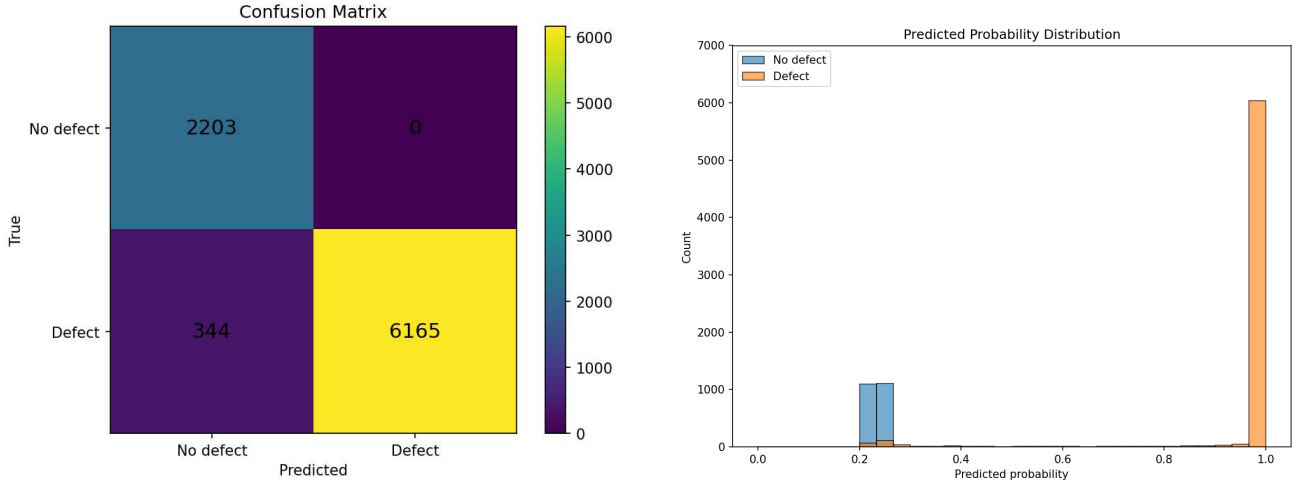
At test time, all samples are first processed by the classifier to obtain defect probabilities and predicted labels. The regressor is then applied only to samples classified as defected, because geometry estimates are meaningful only after a defect has been identified. Classification performance is evaluated on the full test set. Regression performance is reported on true defect samples to isolate sizing accuracy from classification errors. Additional analyses are carried out using defect angle and scan radius as grouping variables for visualization only.

Overall, this two-stage structure is well aligned with the underlying physics and dataset organization. The classification stage determines whether the multi-frequency magnetic signature indicates the presence of corrosion. The regression stage estimates defect geometry once a defect is identified. In this sense, the CNN and MLP serve complementary roles. The CNN acts as an axial feature extractor for defect-sensitive spatial patterns, whereas the MLP acts as a compact nonlinear estimator that maps the complete defected signature to continuous geometric parameters. Because both models rely solely on the measured magnetic channels, the learned representation is driven directly by the electromagnetic response.

4 Results and Discussion

On the held-out test set, the classifier achieves an accuracy of 96.05%, a precision of 100.00%, a recall of 94.72%, and an F1-score of 97.29%. On the defect-only test subset, the regressor achieves R^2 values of 0.9582 for defect depth fraction, 0.9228 for width, and 0.8349 for length. The evaluation is in-distribution because the training and test samples are synthetic data generated from the same semi-analytical model family.

Shown in Fig. 5 is the classification performance over the full held-out test set. The classifier produces zero false positives on the evaluated test set, corresponding to a precision of 100.00%. Because the training and test samples are generated by the same semi-analytical forward model with prescribed defect families and bounded synthetic noise, the zero-false-positive result characterizes in-distribution discrimination and should not be interpreted as a forecast of field false-positive rates. In the probability histogram, non-defect cases are concentrated in a narrow low-probability band, while defect cases are concentrated close to probability 1.0, with only a small overlap region. The probability separation and the 97.29% F1-score quantify the defect-separation capability of the four-channel low/high-frequency representation under the present synthetic conditions.



(a) Confusion matrix.

(b) Predicted probability distribution.

Figure 5: Classification results for the two-stage learning framework. The evaluated test set has zero false positives, and the predicted-probability distribution separates most intact and defected samples.

Metric	Value
Accuracy	96.05%
Precision	100.00%
Recall	94.72%
F1-score	97.29%

Table 3: Classification performance on the held-out test set.

Regression performance is summarized in Fig. 6. These metrics are computed over the full defect-only test subset rather than from a single representative example, so they reflect aggregate sizing performance across the simulated defect geometries included in the dataset. The depth-fraction prediction achieves an R^2 value of 0.9582, with a mean absolute error (MAE) of 0.0321 and a root-mean-square error (RMSE) of 0.0526.

The width prediction achieves an R^2 value of 0.9228, an MAE of 0.00593 m, and an RMSE of 0.00796 m. The corresponding scatter plot shows a clear positive trend and relatively tight clustering around the ideal agreement line.

The length prediction is more difficult than depth and width in this test set, with an R^2 value of 0.8349, an MAE of 0.00923 m, and an RMSE of 0.0116 m. Compared with the depth and width predictions, the length estimates exhibit broader scatter while still preserving a positive relationship between true and predicted values.

The R^2 values and scatter trends demonstrate that the multi-frequency magnetic-field representation contains quantitative information about defect geometry under the synthetic conditions considered here. The observed ordering of target accuracy is reported as an empirical finding from the present test set; identifying the underlying sensitivity mechanisms would require a separate forward-model sensitivity analysis.

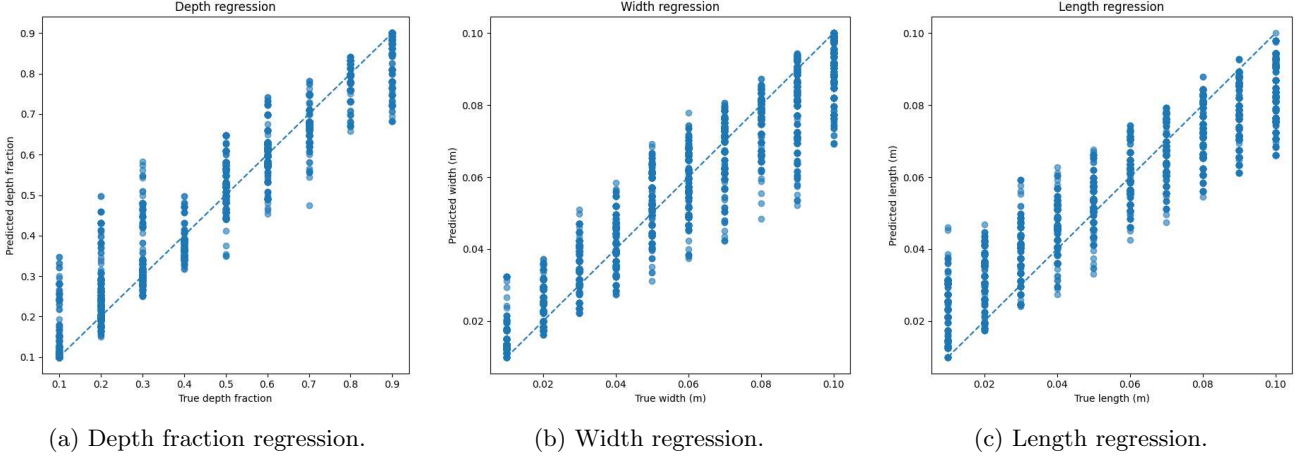


Figure 6: Regression performance for defect depth fraction, width, and length. The scatter plots compare predicted and true values on the defect-only test subset.

Geometry-conditioned classification results provide additional insight into detectability. Shown in Fig. 7(a) is the accuracy heatmap over defect width and length. The lowest width and length bins have reduced accuracy, consistent with the smaller perturbation amplitudes produced by smaller defect dimensions. Accuracy increases as the defect dimensions increase, and the moderate-to-large defect region has values close to 100% over most of the parameter space.

The same trend is summarized in Fig. 7(b), where accuracy is plotted as the characteristic defect size increases. The characteristic defect size is defined in terms of a threshold k : a defect is included at size k when both its length and its width are at least k , that is, when the smaller of the defect length and width is at least k . Accuracy rises from approximately 94.7% at the smallest evaluated size threshold to nearly 100% for larger sizes, and it reaches 100% once the characteristic length and width scale exceeds roughly 70 mm. Within the present synthetic sweep, the magnetic signatures become more separable as the defect width and length increase.

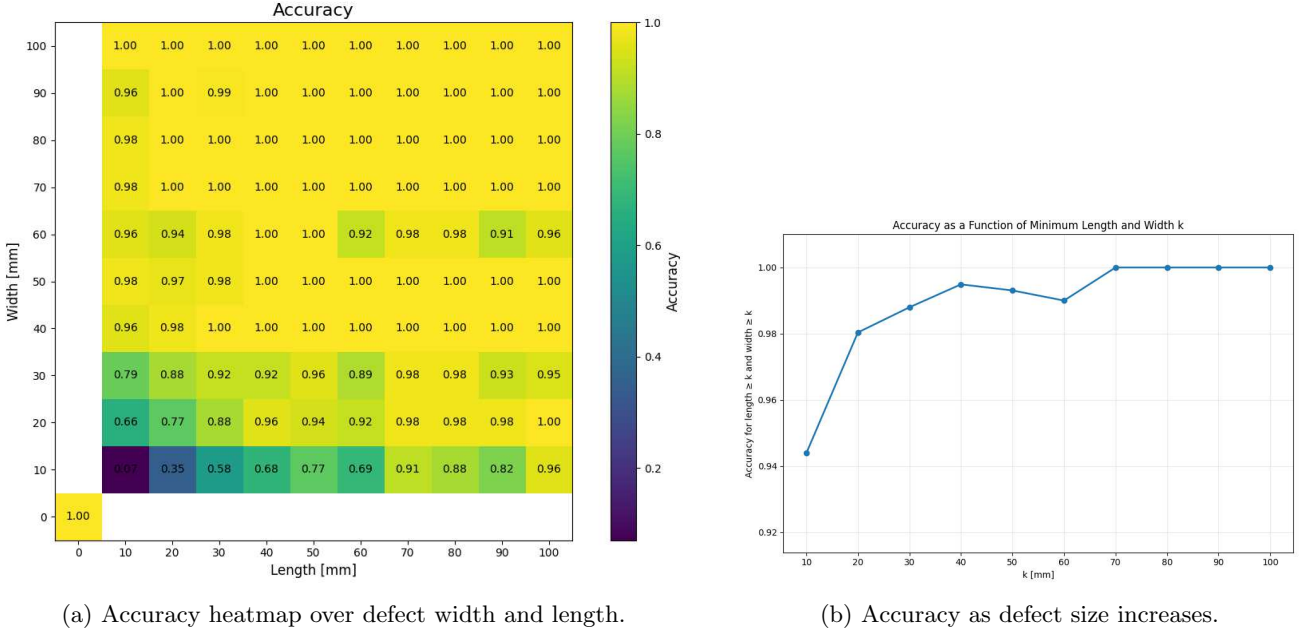


Figure 7: Geometry-conditioned classification performance. Detection accuracy increases with defect width and length in the synthetic parameter sweep.

The reported learning results should be interpreted together with the assumptions of the synthetic study. The finite-element comparison verifies that the semi-analytical model reproduces the perturbation trends used for data generation, while the classification and regression metrics show that the generated four-channel signatures are learnable by the two-stage model. Several limitations should nevertheless be noted. The forward model adopts an idealized long-pipe geometry, homogeneous material properties, and simplified surrounding conditions. It also represents corrosion using regular parameterized defect shapes rather than the full irregular morphology of field corrosion. In addition, the learning models are trained and tested on synthetic data generated from the same

physics-based model family. The reported performance should therefore be interpreted as a physics-informed proof of concept rather than a field-validated deployment result. Real inspections may introduce additional variability through soil properties, coatings, current-return paths, magnetometer bias or drift, positioning uncertainty, and defect shapes not represented in the present dataset. Experimental validation and domain-gap assessment therefore remain the most important next steps before field deployment.

5 Conclusion

Building on the earlier finite-element-based study of above-ground electromagnetic pipeline inspection [20], the present work introduces a semi-analytical magnetic-flux-density model, a synthetic data generator built on it, and a two-stage learning framework for defect detection and sizing. The semi-analytical model combines a Bessel-function annulus solution for skin-effect current density with a Biot–Savart perturbation formulation for finite-length outer-surface defects. The model reproduces the finite-element trends within the agreement metrics reported in Section 3, including the defect-centered perturbation shape and the frequency-dependent change in magnetic response.

Using this forward model, a multi-frequency synthetic dataset is generated in which each inspection case contains 11 axial scan points and four magnetic-field channels. The dataset spans defect depth, length, width, circumferential angle, and scan radius, with class labels defined consistently with the simulated defect geometry. A two-stage learning strategy is then applied to these signatures: a binary classifier detects defects, and a defect-only regressor estimates defect depth fraction, width, and length.

On the held-out synthetic test set, the classifier achieves 96.05% accuracy, 100.00% precision, 94.72% recall, and a 97.29% F1-score. The regression stage achieves R^2 values of 0.9582 for depth fraction, 0.9228 for width, and 0.8349 for length on the defect-only test subset. The classification and regression metrics demonstrate that the four-channel multi-frequency magnetic representation contains learnable information for both defect detection and sizing under the simulated conditions considered here.

The reported learning performance should be interpreted as in-distribution synthetic-data performance rather than field-validated inspection accuracy. Training and testing are performed on data generated from the same semi-analytical model family, with regular parameterized defect geometries and bounded synthetic noise. Experimental validation against measured above-ground magnetic data and assessment of the simulation-to-field domain gap are therefore the necessary next steps.

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Data Availability

The dataset generated and analyzed during the current study consists of synthetic multi-frequency magnetic-field signatures produced by the semi-analytical forward model described in the manuscript. It is available from the corresponding author on reasonable request, and it can be regenerated from the model equations and parameter sweep specified in the paper.

Competing Interests

The authors have no competing interests to declare that are relevant to the content of this article.

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