Advancing Power Magnetic Materials Modeling through Attention-based U-Net with Linear Conditioning

Syed Irfan Ali Meerza, Kody Froehle, Han (Helen) Cui, Daniel Costinett, Jian Liu .

***Abstract*—The evolution of power electronics is fundamentally constrained by the performance of magnetic components, accounting for substantial cost and loss in power converters. The MagNet Challenge spearheads the quest for breakthroughs in the modeling and design of power magnetics, where traditional methods like the Steinmetz Equation, despite upgrades, fall short in accuracy and adaptability. This report proposes a novel and data-driven framework that synergizes empirical modeling with contemporary computational techniques. Our approach seeks to refine the predictive precision of core loss in magnetic materials under varying operational conditions and to expedite the design process, significantly reducing development cycles and reliance on extensive engineering expertise. Central to our methodology is a sophisticated deep learning model, innovatively based on a metadata-conditioned U-Net architecture enriched with attention mechanisms. This model is specifically designed to adapt to the intricate and varying nature of magnetic materials and operational environments. We further refine the model's robustness through noisy-supervision-based self-training, a strategy that ensures its effectiveness on unseen test data. By transcending the constraints of traditional magnetic component modeling, the proposed framework of power magnetic materials modeling not only offers a more efficient and tailored design process but also sets the stage for the next generation of power electronics.**

I. Introduction

Magnetic components are lossy and bulky in power converter systems, which has become a main bottleneck for the new generation of high-performance power conversion systems. The non-linear nature of magnetic materials and the variability introduced by manufacturing processes thwart traditional modeling efforts. Current empirical models, while foundational, offer limited accuracy, and the dynamic operational conditions—spanning temperature, frequency, and DC bias—exacerbate the challenge. Consequently, the power electronics field yearns for a rapid and precise modeling technique that can streamline the design process and reduce the reliance on extensive engineering expertise.

In addressing the MagNet Challenge, our team has developed a hybrid machine learning framework, integrating several advanced components, including data augmentation via Generative Adversarial Networks (GAN) [1], metadata-conditioned attention-based U-Net [2], noisy supervision [3], and knowledge distillation [4]. The framework initiates with the implementation of GAN-based data augmentation, tailored to fulfill the enhanced data volume requisites imperative for efficient model training. Subsequently, the framework augments the attention-based U-Net [5] by assimilating metadata (e.g., temperature, frequency, and waveform type) through the application of cost-effective affine transformations on feature maps.

Moreover, a pivotal element of our methodology is the incorporation of a self-supervised learning paradigm. This paradigm is primarily focused on exploiting the latent supervisory signals inherent in unlabeled data, particularly from testing materials, to refine the model's adaptability to new datasets. Furthermore, we employ knowledge distillation techniques to effectively reduce the model size, ensuring a more efficient and deployable solution. The overarching objective is to realize substantial performance gains with minimal manual intervention, leveraging the intrinsic supervisory characteristics within the testing materials for model refinement.

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II. Preliminaries

A. 1-Dimensional Generative Adversarial Network (GAN)

Generative Adversarial Networks (GANs) in a one-dimensional (1-D) setting are a simplified version of the standard GAN framework. They consist of two neural networks, the Generator (G) and the Discriminator (D), that are trained simultaneously through adversarial processes. The generator aims to produce data that is indistinguishable from real data, while the discriminator strives to accurately distinguish between real and generated data. The adversarial training of these networks is orchestrated by a loss function that encapsulates their tug-of-war:

$$\min_G \max_D V(D,G) = \mathbb{E}_{x_{p_d}}[\log D(x)] + \mathbb{E}_{z_{p_z}}[\log(1 - D(G(z)))], \tag{1}$$

where $\mathbb{E}_{x\sim p_d}[\log D(x)]$ represents the expected log-probability that the discriminator assigns to real data being authentic, while $\mathbb{E}_{z\sim p_z}[\log(1 - D(G(z)))]$ captures the expected log-probability that the discriminator assigns to fake data being inauthentic. The generator's goal is to minimize this function, thereby generating data that is increasingly likely to be classified as real by the discriminator. In our approach, we leverage 1D GAN to expand limited datasets, allowing for the development of models that predict magnetic behavior with enhanced accuracy.

B. U-Net with GRU

Integrating Gated Recurrent Units (GRUs) [6] into a U-Net architecture for sequence-to-sequence (*seq2seq*) generation represents a significant adaptation from its traditional applications. In this variant, both the encoder and decoder components of the U-Net are constructed using GRU layers. This design allows the model to effectively handle sequential data, such as Magnetic Flux Density and Magnetic Field Intensity.

In the encoder part of the U-Net, GRUs process the input sequence, creating a compressed representation that captures the temporal context and dependencies within the data. This encoded information is then passed through the bottleneck of the network and subsequently fed into the decoder. The decoder, also composed of GRU layers, aims to reconstruct or transform the sequence into the desired output format, maintaining the sequence's integrity and contextual relevance. The skip connections, a hallmark of U-Net architecture, are adapted here to connect corresponding GRU layers in the encoder and decoder, allowing for the transfer of temporal context directly across the network, which is particularly beneficial for complex *seq2seq* tasks.

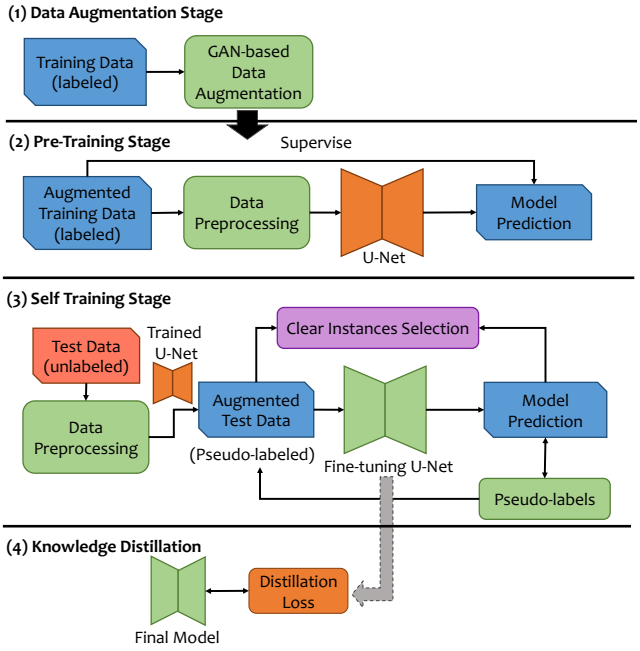

Fig. 1. Framework Overview.

C. Knowledge Distillation

Knowledge distillation [4] is a technique in machine learning where a smaller, less complex model (the "student") is trained to replicate the behavior of a larger, more complex model (the "teacher"). This process involves using the outputs of the teacher model as an additional training signal for the student. The rationale behind knowledge distillation is that the student model, while smaller and more computationally efficient, can learn to perform similarly to the teacher by mimicking its output patterns. This approach is particularly useful for deploying models in resource-constrained environments like mobile or embedded systems, where the balance between model size and performance is critical.

The process typically involves training the teacher model to its full capacity on the training data and then using its predictions to train the student model. The student learns to mimic the teacher's outputs by minimizing a distillation loss function that signifies the divergence between the teacher's and student's output distributions. The student's loss function is like below:

$$\min \mathcal{L} = \alpha \cdot H(y, z_S/T) + (1-\alpha) \cdot D_{KL}(z_T/T, z_S/T), \quad (2)$$

where $\mathcal{L}$ represents the total loss, H denotes the Mean Squared Error (MSE) loss, y is the true output, z_S and z_T are the outputs from the student and teacher models respectively, T is a temperature parameter utilized for softening the probabilities, D_{KL} signifies the Kullback–Leibler divergence, and α is a balancing factor for the two components of the loss function.

III. Framework Overview

As shown in Fig. 1, our framework involves a four-stage process, each stage building upon the insights and outputs of the previous one. This structured approach ensures a comprehensive development and refinement of the model, tailored to effectively handle diverse and complex datasets. The stages are as follows:

(1) Data augmentation stage. Initially, we focus on diversifying the training data through the data augmentation stage. We utilize a 1D GAN, trained on the provided training dataset, to create additional data points. These synthetic points closely resemble the original data distribution, thus expanding the dataset and boosting the model's capability to generalize to new, unseen data.

(2) Pre-training stage. Following augmentation, the augmented dataset is then utilized to *pre-train* an Attention-based Affine Transformation (AfT) U-Net (Section IV-B). This stage is standard supervised learning, where the model is trained using labeled, augmented training data.

(3) Self-training stage. Due to the potential distribution bias between the training and test datasets, the model trained on the training set might not provide optimal performance on the test set. This stage is used for elevating the pre-trained model to higher performance levels on the test dataset. Specifically, in this stage, we will utilize the pre-trained model's predictions on the test data as pseudo-labels. This approach is designed to fine-tune the model, thereby tailoring it more effectively to the characteristics of the test set. A small-loss strategy is employed to select the most reliable instances and their corresponding pseudo-labels, which then guide the fine-tuning process. The iterative refinement of the model parameters and pseudo-labels during this stage results in a significantly enhanced model, specifically optimized for the test dataset.

(4) Knowledge distillation stage. The final stage involves knowledge distillation, where the insights and capabilities of the fine-tuned, larger model are transferred to a smaller, more efficient variant. In this process, the larger model serves as a 'teacher', providing outputs for both the training and test datasets, while the smaller 'student' model learns to replicate

these outputs. This knowledge transfer is crucial for creating a compact model that retains the high performance of its larger predecessor.

Together, these stages represent a holistic and effective strategy for model development, ensuring that each phase contributes to the creation of a robust, high-performing model adept at handling the complexities of material data.

IV. Framework Design

A. GAN-based Data Augmentation

Limited training data often poses a significant challenge in machine learning, particularly for models like U-Net, which can become prone to overfitting where the model learns the specifics of the training data, including its noise and outliers, too precisely, leading to poor generalization on new, unseen data. This issue is especially acute when the available training dataset is small, as is often the case. To address this, we employed a 1D Generative Adversarial Network (GAN) to generate synthetic data samples, enhancing our dataset's diversity and size. This approach ensures that the synthetic data closely mirrors the real data's distribution.

Given that our dataset comprises three types of waveforms, we opted for a conditional 1D GAN, allowing us to exert control over the generated data based on the type of waveform. This conditionality is crucial for maintaining consistency and relevance in the synthetic data. During the GAN's training phase, we meticulously concatenated various components – the B signal, H signal, frequency, and temperature – into a single vector. This comprehensive approach ensures that the generated data not only mimics the real data in terms of distribution but also respects the intrinsic properties and relationships inherent in the original dataset. As a result, the augmented dataset provides a more robust foundation for training the U-Net model, significantly improving its performance and generalizability on unseen data.

B. Attention-based U-Net with Linear Conditioning

In enhancing the sequence-to-sequence (*seq2seq*) capabilities of the U-Net architecture, we leverage the Affine Transformation technique, an innovative approach originally used in visual question answering. This technique significantly augments the network's ability to integrate and process metadata, a crucial element in our application, which includes information such as frequency, temperature, and the type of input wave (sine, triangular, or trapezoidal). To accurately determine the type of input wave, we take the second-order derivative of the input signal. This technique yields distinct responses for different waveforms—a sine wave response for sinusoidal inputs, two spikes for triangular waves, and more than two spikes for trapezoidal waves. By counting these spikes, we can effectively identify the type of the input waveform. This metadata integration is key to achieving more accurate and contextually relevant *seq2seq* generation.

Our model's architecture is based on a 2D U-Net as shown in Fig. 2, designed to handle dual inputs: magnetic flux density and the one-hot encoded metadata. The Affine Transformation (AfT) layers, in synergy with a dedicated generator, are tasked

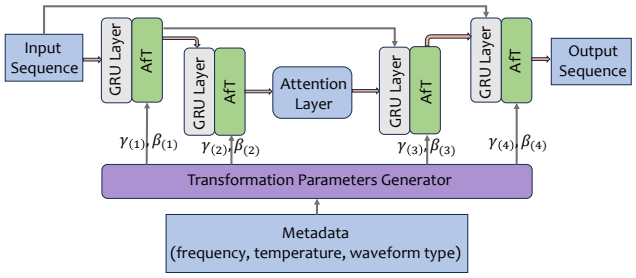

Fig. 2. Attention-based U-Net with Linear Conditioning.

with conditioning the neural network using this metadata. Central to the AfT layers' functionality are the $\gamma(i)$ and $\beta(i)$ parameters, which linearly modulate the inputs of each AfT layer. These parameters are generated by a specialized Transformation Parameters Generator, featuring two hidden layers with 64 and 16 neurons, respectively. The generated γ and β values, unique for each filter, are applied to modulate the GRU feature maps within the AfT layers, ensuring that each layer's output is finely tuned in accordance with the metadata. Shared weights across the generator enhance learning efficiency, maintaining a consistent feature extraction from the metadata. Additionally, the sigmoid activation confines the values between 0 and 1, ensuring a controlled modulation effect.

In addition, an attention layer has been strategically integrated to bridge the encoder and decoder part of the U-Net. This layer refines the model's focus, allowing it to focus on salient features and sequences. It enhances the network's performance in handling complex dependencies and contextual variations, which is particularly beneficial in our seq2seq tasks.

C. Self-training Adaptation

To improve the model's ability to generalize to new, unseen test data, we employ the concept of noisy supervision [3]. This semi-supervised learning method is designed to leverage unlabeled test datasets in this MagNet challenge, enabling the model to better adapt to these test sets. This approach is highly beneficial in scenarios where there is a mix of labeled and unlabeled data. In our case, the training data are labeled while the testing data remain unlabeled. Noisy supervision facilitates learning from both labeled and unlabeled data, enhancing the model's adaptability. This is crucial in addressing the challenge of domain shift, a prevalent issue where a model trained in one setting underperforms in a different one.

In this process, the pre-trained model, trained on the labeled training data, attempts to generalize its learning to the target domain (i.e., test sets) through self-training. Particularly, the model first performs regular model prediction on the test datasets and generates pseudo-labels (i.e., H signals). Initially, the model's performance on the test dataset is suboptimal due to the potential distribution bias between the training and test datasets. We thus purify the obtained pseudo-labels through a clean instances selection strategy, choosing only the fraction of the instances that produce small losses to supervise the self-training process.

In addition, deep networks tend to initially fit into clean or "easy" instances in the early training epochs and later start adapting to noisy or "hard" instances. To optimize this training process, we introduce $R(T)$, which adjusts the fraction of data instances utilized for self-training at each training epoch T. Initially, $R(T)$ is set to 1, meaning all instances are included, as early in training, deep networks are less prone to memorize noise, making the full dataset beneficial for learning. However, as training advances, $R(T)$ is systematically decreased. This is in response to the tendency of networks to begin overfitting to noisy data, typically indicated by higher losses. By progressively reducing $R(T)$, we prioritize training on cleaner, more reliable data, effectively mitigating the risk of the networks overfitting to noisy labels with increasing epochs.

Our strategy for selecting clean instances in the self-training stage is crucial in reducing error rates in pseudo-labels, ensuring cleaner supervision. This ongoing refinement of pseudo-labels, coupled with repeated learning from the test dataset, enables the model to progressively achieve satisfactory performance, adeptly adapting to the specific features of the target domain.

D. Framework Workflow

Our methodology, meticulously tailored for each type of material, employs a four-stage training process to optimize model performance for each specific material. The initial stage, focused on augmentation, leverages a 1D GAN network to enhance the raw training data. This involves training the GAN to replicate the unique distribution of the training data, followed by generating 3,000 to 5,000 synthetic data samples specific to each material type. These samples are then amalgamated with the original training data, creating a comprehensive, augmented training dataset. This enriched dataset serves as the foundation for pre-training an Attention-equipped Affine Transformation (AfT) U-Net model, setting the stage for subsequent steps.

The second stage continues with pre-training the U-Net model using the augmented dataset. Before training, we normalize the dataset using the mean and variance of the dataset. This training is a standard supervised learning where the model is trained using labeled augmented data.

In the third stage, we infer the pre-trained U-Net model on the test dataset to extract pseudo-H signals. These signals, once integrated with the test dataset, form an augmented test dataset. This dataset, combined with the augmented training dataset, culminates in a custom dataset tailored for each material, bridging the gap between training and real-world application. This stage involves fine-tuning the pre-trained U-Net model through a self-training approach. Here, the custom dataset is used to refine the model, focusing on updating it based on select low-loss instances. This selection is strategically governed by an instance selection algorithm, which dynamically adjusts the number of instances chosen, starting with a higher count and progressively reducing it.

In the final stage, we implement knowledge distillation to impart insights from the fine-tuned U-Net model to a smaller, more efficient version of the AfT U-Net with attention. This ensures that the smaller model maintains the high-performance characteristics of the larger model while being better suited for scenarios demanding computational efficiency. This comprehensive, multi-stage approach not only facilitates effective learning from the available data but also optimizes the model for enhanced performance and efficiency, particularly on unseen data.

TABLE I
NUMBER OF MODEL PARAMETERS

Material	A	B	C	D	E
Number of Parameters	23,000	23,000	23,896	32,546	25,990

V. MODEL SIZE

Table I shows the number of parameters for the five models we developed, each corresponding to one of the five materials.

VI. CONCLUSION

In conclusion, our hybrid machine learning framework represents a significant stride forward in addressing the challenges posed by the non-linear nature and variability of magnetic materials in power conversion systems. By judiciously combining advanced techniques like GAN-based data augmentation, metadata-conditioned attention-based U-Net, noisy supervision, and knowledge distillation, we have crafted a solution that not only enhances modeling accuracy but also simplifies the design process in power electronics. The incorporation of self-supervised learning paradigms and the exploitation of latent supervisory signals in unlabeled data are particularly notable for their roles in improving the adaptability of the model to new datasets. This framework adeptly handles the dynamic operational conditions and variability inherent in magnetic components, reducing the reliance on extensive empirical models.

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