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Fringe pattern images for disruptive structured data classification

Imágenes de franjas para clasificación disruptiva de datos estructurados

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Abstract

Conventional models often fall short in supporting decision-making from structured tabular data, as they struggle to capture complex feature interactions and nonlinear dependencies. In contrast, convolutional neural networks (CNNs), highly effective in computer vision, remain underutilized in structured data analysis. This work introduces a disruptive data science approach that bridges this gap by transforming tabular records into fringe pattern images through Gaussian surface modeling. These images encode feature intensity, spatial frequency, and phase-based texture, enabling CNNs to exploit

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new visual cues beyond raw numerical inputs. The method is systematically evaluated across architectures such as ResNet, DenseNet, and GoogleNet using the PIMA Indians Diabetes dataset as a benchmark. Experimental results show that the proposed fringe-based visual representation consistently outperforms baseline classifiers, achieving higher accuracy and richer feature discrimination. By reframing structured data as visual information, this approach demonstrates how disruptive applications of data science can enhance healthcare, finance, and industrial analytics, fostering models that are both more accurate and more interpretable.

Keywords: Data science, structured data, visual representation, fringe patterns, deep learning.

Resumen

Los modelos convencionales de clasificación suelen ser insuficientes para apoyar la toma de decisiones con datos estructurados en formato tabular, ya que presentan limitaciones al capturar interacciones complejas y dependencias no lineales. En contraste, las redes neuronales convolucionales (CNN), altamente efectivas en visión por computador, permanecen subutilizadas en el análisis de datos estructurados. Este trabajo introduce un enfoque disruptivo en ciencia de datos que transforma registros tabulares en imágenes de patrones de franjas mediante modelado de superficies gaussianas. Estas imágenes codifican intensidad de atributos, frecuencia espacial y textura basada en fase, lo que permite a las CNN aprovechar nuevas señales visuales más allá de los valores numéricos originales. El método se evalúa en arquitecturas como ResNet, DenseNet y GoogleNet utilizando como referencia el conjunto de datos PIMA Indians Diabetes. Los resultados experimentales muestran que la representación visual propuesta supera de forma consistente a los clasificadores convencionales, logrando mayor precisión y discriminación de características. Al replantear los datos estructurados como información visual, este enfoque evidencia cómo las aplicaciones disruptivas de la ciencia de datos pueden potenciar áreas como la salud, las finanzas y la analítica industrial, fomentando modelos más precisos e interpretables.

Palabras clave: Ciencia de datos, datos estructurados, representación visual, patrones de franjas, aprendizaje profundo.

1. Introduction

The rapid expansion of data-driven innovation has established data science as a key catalyst for disruptive applications in domains such as healthcare, finance, and industrial operations. Within these fields, structured data, most organized in tabular formats with measurable attributes per record—serves as the backbone of decision-making and provides fertile ground for the development of new analytical methods and intelligent tools [1], [2]. Fully exploiting this potential requires not only efficient classification algorithms but also innovative approaches capable of uncovering complex, latent relationships that traditional techniques often fail to detect.

Classification, as a fundamental task in data science, underpins many decision-making processes by allowing data instances to be systematically assigned to predefined categories based on their characteristics. This capability is critical because accurate classification not only enables organizations to interpret complex information but also supports predictive analytics, automation, and strategic decision-making across diverse domains. Conventional machine learning models—such as decision trees, logistic regression, and SVM—have shown adequate performance in many classification scenarios [3], [4]. However, their ability to process low-dimensional datasets is limited due to restricted variability and difficulty in modeling non-linear feature interactions [5], [6]. These constraints highlight a disruptive research question for data science: *Can visual transformations of structured data enhance the classification performance of deep learning models and create new opportunities for disruptive applications?*

To address this challenge, researchers have increasingly explored enhanced data representations. Deep learning models, particularly convolutional neural networks (CNNs), excel at extracting non-linear and hierarchical patterns [7], [8]. To leverage these capabilities, one-dimensional tabular records have been transformed into two-dimensional images using approaches such as spectrograms, recurrence plots, spatial correlation maps, and basic geometrical distributions [9], [10], [11]. These visual encodings allow CNNs to operate on non-traditional data formats, aligning structured data with spatial-processing architectures and resulting in superior performance compared to conventional classifiers. Moreover, hybrid strategies that combine CNN-based feature extraction with classifiers like SVM have demonstrated improvements in both accuracy and interpretability [12].

This trend underscores disruptive opportunities for data science, not only as an applied discipline but also as a transformative force for innovation. In medicine, visual encodings of clinical variables have enhanced diagnostic support systems, improving early detection and enabling more personalized treatments [5], [13]. In industry, the visualization of sensor data has strengthened fault detection and predictive maintenance, reduced downtime and increasing operational efficiency [11]. These examples demonstrate that reframing structured data through visual paradigms extends beyond methodological novelty; it redefines how organizations can build decision-support systems that are more robust, interpretable, and scalable across domains, opening new avenues for disruptive applications of data science.

Building on these advances, this paper introduces a novel visual representation method for structured data classification. Specifically, we propose converting tabular inputs into fringe pattern images from Gaussian surface mappings, as illustrated in Figure 1. These images are produced in both grayscale and RGB formats. They embed feature importance, spatial frequency, and phase-based texture into a structure optimized for CNN learning. This transformation provides convolutional models with novel cues beyond raw numerical inputs, enabling richer feature discrimination. The objective of this study is to evaluate whether this encoding strategy improves classification performance compared to conventional approaches. The proposed method is validated using the PIMA Indians Diabetes dataset and benchmarked against classical machine learning classifiers and a previously reported rectangular image representation baseline [11].

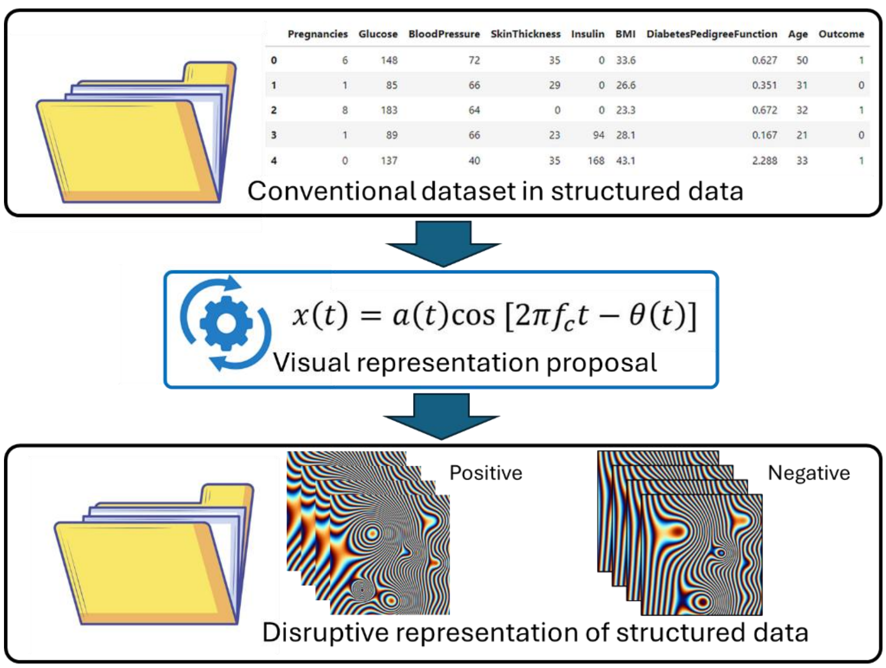


Figure 1. Visual representation process for structured data transformation.

The remainder of this document is as follows: Section II presents the theoretical foundation of visual representation and CNN architecture; Section III details the methodology, including dataset transformation and model evaluation; Section IV analyzes the experimental results and compares the performance of the proposed approach to baseline methods; and Section V provides concluding remarks and outlines future research directions.

2. THEORETICAL FRAMEWORK

2.1. Visual representation of structured data

The visual representation of structured data refers to the transformation of one-dimensional tabular records into two-dimensional image formats suitable for processing by convolutional neural networks (CNNs). This transformation expands the analytical horizon of data science, enabling computer vision models to operate in domains where information is traditionally encoded in purely numerical form. The process typically begins with normalization, followed by a mapping strategy that encodes feature intensity as pixel values within an image. Depending on the encoding design, the resulting images can be generated in grayscale or extended to RGB formats, which enhance spatial and textural diversity and allow CNNs to capture more complex feature interactions.

CNNs are considered highly effective in computer vision because they exploit spatial hierarchies of patterns through convolutional filters, enabling them to detect edges, textures, and progressively more abstract representations with remarkable efficiency. Their success is evidenced across multiple benchmark datasets: in ImageNet, models such as AlexNet, VGG, and ResNet reduced classification error rates to levels below 5%; in MNIST and CIFAR-10, CNNs achieved accuracy exceeding 99% and 96%, respectively, setting standards for digit and object recognition. Beyond benchmarks, CNNs have transformed real-world applications such as medical imaging (early detection of tumors in MRI and CT scans), autonomous vehicles (real-time object detection and scene understanding), and facial recognition systems (widely deployed in security and authentication). These achievements highlight the disruptive potential of adapting visual encodings of structured data, as they allow CNNs to transfer their proven strengths in computer vision to domains traditionally dominated by purely numerical approaches.

In this study line, previous works have investigated alternative visual encodings such as spectrograms, recurrence plots, and correlation maps, particularly for the conversion of temporal or physiological signals into images. These approaches have demonstrated that structured inputs, once represented as visual patterns, can be effectively leveraged for CNN-based classification. Figure 2 illustrates one such transformation pipeline applied to personal identification from electrocardiogram signals (EEG), inspired from [14] as part of the theoretical foundation reviewed in this study.

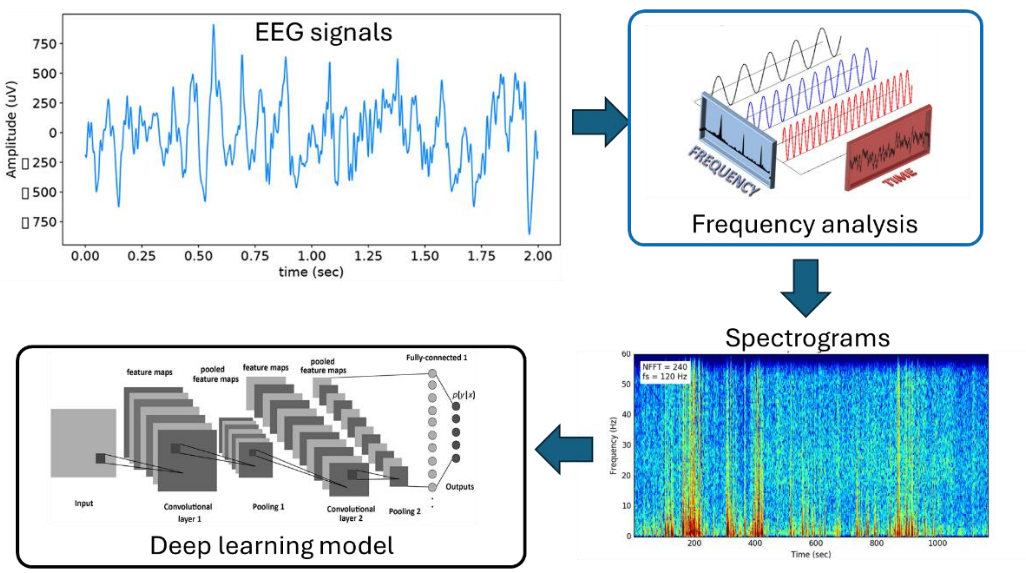


Figure 2. Schematic representation of EEG signal recognition using spectrogram-based representation.

Another visual representation considered in this study is the rectangular layout proposed in [5], which organizes features into a two-dimensional image according to their statistical importance. This method establishes a spatial ranking of variables to maximize coherence and facilitate pattern recognition through convolutional filters. Although not developed as part of the proposed method, it was reproduced in this work to serve as a baseline for the comparative evaluation of visual encoding techniques. Figure 3 illustrates the original transformation process, referred to as the Expansion Flow Model – Base Line, as presented in [5].

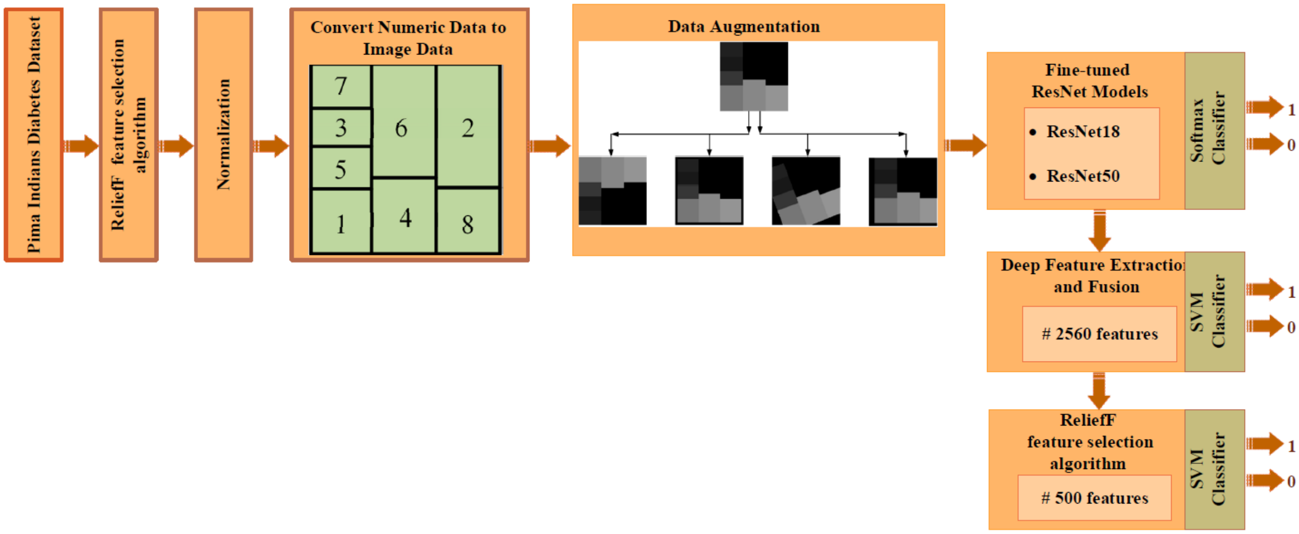


Figure 3. Schematic representation of structured data using rectangle spatial distributions.

2.2. Fringe pattern images

Fringe pattern projection is a well-established technique in optical metrology, traditionally used to reconstruct the geometry of physical surfaces by projecting structured light—such as square waves or sinusoidal signals—onto an object and analyzing the distortions in the resulting patterns [15]. Through this principle, the topographic features of a surface can be inferred, as illustrated in Figure 4, where deformed fringes reveal variations in curvature [16].

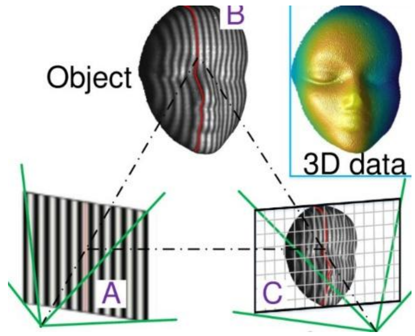


Figure 4. Schematic representation of fringe pattern images in 3D reconstruction.

Recent advances have extended this concept beyond its physical origins toward computational applications. Instead of projecting light onto real objects, synthetic fringe maps can be generated digitally, enabling their use as a visual encoding of complicated experimental assemblies. By modulating pixel intensity with periodic functions, fringe-based images introduce spatial textures that enrich the original data representation, thereby facilitating pattern recognition by convolutional neural networks (CNNs) [17]. Figure 5 illustrates how 3d surfaces are presented as synthetic 2D data in gray levels, and how they can be represented as color fringe patterns.

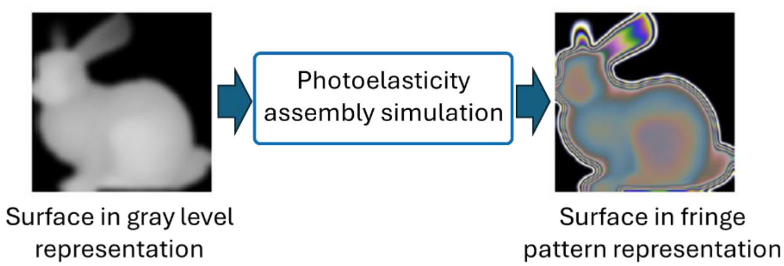


Figure 5. Synthetic fringe patterns from 2d surface representations.

2.3. Deep learning architectures in visual representation

Deep learning has emerged as a transformative branch of machine learning, capable of modeling complex, non-linear relationships through multilayer neural architectures. Its potential lies in the automatic extraction of high-level features directly from raw data, reducing the need for manual preprocessing and domain-specific engineering. Recent trends include the application of deep learning to multimodal problems, explainable artificial intelligence (XAI), and cross-domain transfer learning, all of which demonstrate its versatility in handling diverse and unstructured information sources [8]. Within this broad spectrum, visual representation problems occupy a central role, as they enable models to exploit spatial structures and discover patterns that traditional statistical approaches often overlook.

Convolutional Neural Networks (CNNs) have become the dominant paradigm in image classification tasks due to their ability to extract and learn hierarchical visual features at multiple levels of abstraction. Their success in computer vision has motivated the exploration of CNNs in non-traditional domains, where structured data are transformed into visual representations to leverage the spatial learning capabilities of these models [8], [18], [19]. In this work, the attention was concentrated on six representative CNN architectures not only for their historical significance but also for their architectural diversity, which provides complementary perspectives on the advantages of convolutional learning: AlexNet, LeNet, VGG, GoogleNet, ResNet, and DenseNet, as summarized in next chart.

Table 1. Conventional deep learning models for visual representation cases.

CNN	Description	Citation
AlexNet	Introduced key innovations such as ReLU activations, dropout regularization, and GPU parallelism, achieving breakthrough performance on ImageNet.	[20]
LeNet	One of the earliest CNNs, provides a lightweight architecture suitable for low-complexity tasks.	[21]
VGG	Adopted a uniform deep structure using 3×3 convolutions and max pooling layers.	[20]
GoogleNet	Incorporated multi-scale convolutions in parallel, reducing parameters while preserving accuracy.	[22]
ResNet	Enabled very deep networks by introducing residual connections to overcome gradient degradation.	[21]
DenseNet	Extended this concept by concatenating outputs from all previous layers, enhancing feature reuse and gradient flow.	[23]

3. METHODS AND PROCEDURES

This study introduces a structured methodology for classifying low-dimensional clinical data through fringe-based visual representations. The case study is the PIMA Indians Diabetes dataset, which includes 768 records and 8 clinical features [5]. The process begins with preprocessing and normalization, scaling each feature to the [0,1] range via Min-Max normalization. From these values, Gaussian-based images of size 224×224 pixels are generated, where the intensity and spread of each Gaussian encode the normalized attributes by considering the importance of feature ranking through random forest strategy. In this case, mor important features imply wider gaussian surfaces. The high gaussian value is the feature value in the dataset. Subsequently, synthetic fringe patterns are created by modulating the Gaussian images with a cosine function, simulating Moiré effects and embedding spatial frequency variations that enrich the visual structure:

$$I\_m = \beta \cos\left(2\pi f\left(Z\left(I_g\right)\right)\right) \tag{1}$$

Where Im is the Moiré fringe image, Ig is the Gaussian input, Z(Ig) the normalization function, f the spatial frequency, and β the modulation amplitude. This operation highlights high-frequency textures while preserving the original feature distribution. To increase information density, the transformation is extended to RGB encoding. Phase shifts are applied independently to each channel (red, green, blue), yielding a multichannel representation:

$$I\_mR = \beta \cos\left(2\pi f\left(Z\left(I_g\right)\right) + \varphi R\right) \tag{2}$$

$$I\_mG = \beta \cos\left(2\pi f\left(Z\left(I_g\right)\right) + \varphi G\right) \tag{3}$$

$$I\_mB = \beta \cos\left(2\pi f\left(Z\left(I_g\right)\right) + \varphi B\right) \tag{4}$$

Where, ImR, ImG, ,ImB are the fringe images generated in the red, green, and blue channels, respectively. Likewise, ϕR, ϕG, ϕB are the phase shifts applied to the red, green, and blue channels. This strategy simulates interferometric behavior and enriches spatial diversity. Figure 6 summarizes the proposed approach.

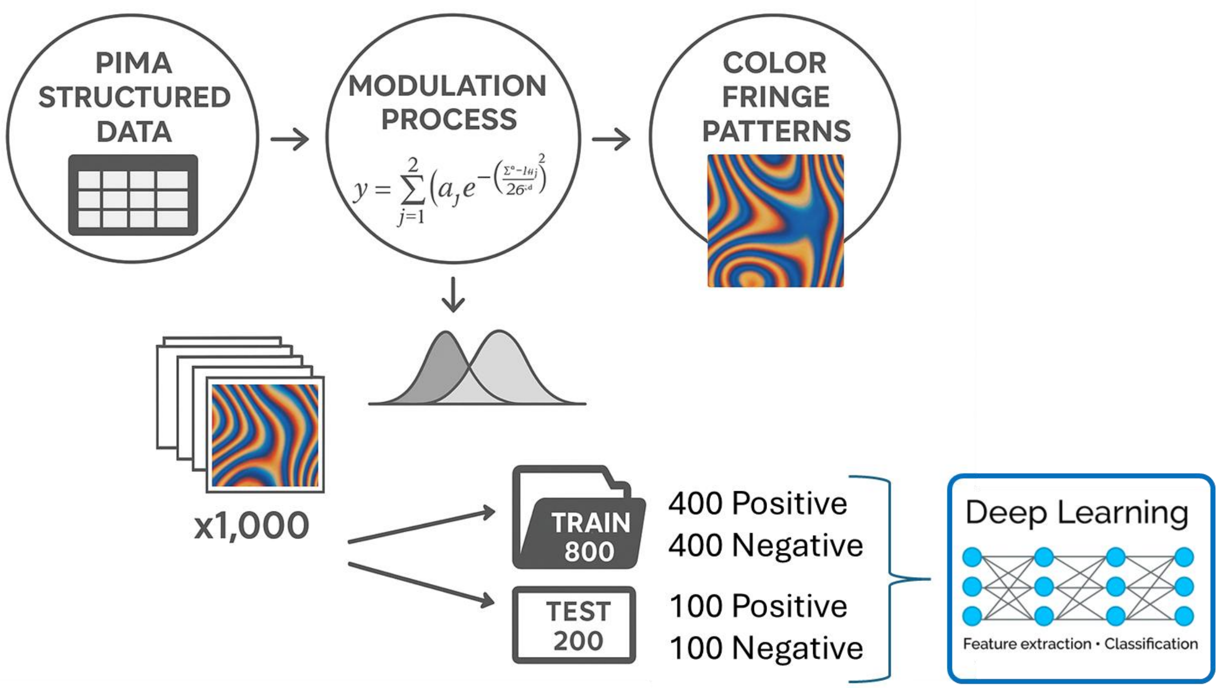


Figure 6. Proposed approach for structures data representation.

The resulting grayscale and RGB images are stored in BMP format via OpenCV, with balanced subsets of 1,000 samples per class. Classification is performed using the architecture reported previously in table 1. In our case, performance is evaluated using Accuracy, Precision, Recall, and F1-score, complemented with pixel-level statistics (mean, standard deviation, entropy, maximum, minimum). These analyses are implemented in Python with NumPy, Pandas, PIL, SciPy, and OpenCV. Finally, results are compared against a rectangular mapping baseline [5], allowing assessment of the added value provided by Moiré-based encodings in structured data classification.

To assess the effectiveness of the proposed method, results are compared with an existing rectangular mapping approach, used as a baseline. This comparative analysis examines whether Moiré and RGB-based transformations improve the deep network's ability to discriminate between classes.

4. RESULTS AND ANALYSIS

From the processing of the structured data and the feature importance ranking obtained through a preliminary classification using a Random Forest model, we identified the attributes that should be prioritized in the visual representation [5]. This initial analysis, conducted on the original PIMA dataset, allowed us to evaluate the relative contribution of each variable to the classification task. The resulting ranking determined the order in which features were spatially arranged in the image encoding. These key features, ordered by relevance, are Pregnancies, Glucose, Blood Pressure, Skin Thickness, Insulin, BMI, Diabetes Pedigree Function, and Age, as illustrated in the following figure.

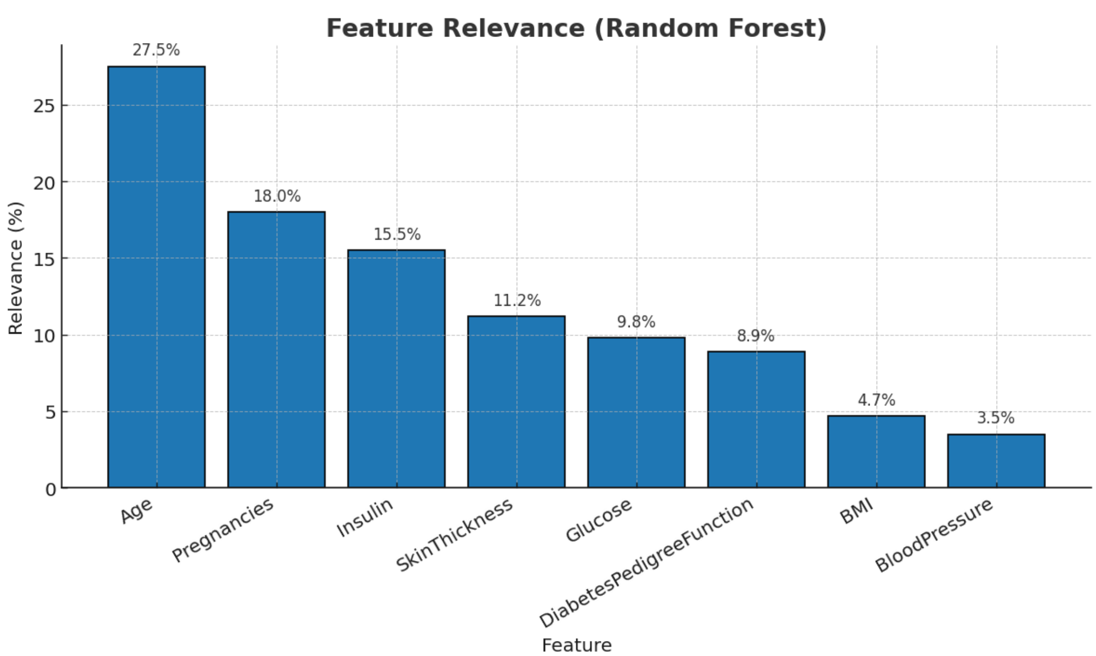
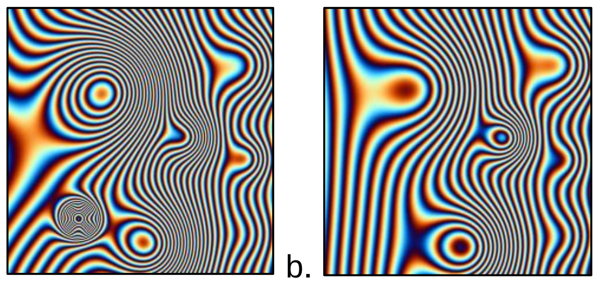


Figure 7. Feature ranking evaluation.

The value of each feature for a given subject modifies the height parameter of the Gaussian-based surface used for visual encoding. This surface is subsequently modulated into a fringe pattern, where variations in amplitude and phase visually reflect the distribution of the original data [17]. The following figure presents two examples of this process for patients with different class labels, demonstrating how individual feature profiles result in distinct visual patterns.



a. b.

Figure 8. Two visual representation cases for positive, and negative patient within the PIMA dataset, respectively.

In relation to previous figures, next table compares clinical features from representative patients in the PIMA dataset. Positive diagnosis cases present higher values in several key attributes such as glucose, blood pressure, BMI, and age leading to more pronounced Gaussian surfaces. Once modulated with cosine functions, these distributions produce Moiré fringe patterns characterized by higher spatial frequency and geometric complexity. In contrast, negative diagnosis cases generate smoother Gaussian profiles and fringe patterns with lower frequency and texture. These visual distinctions emphasize the potential of Moiré-based encoding to highlight clinically relevant patterns and improve class separability.

Table 2. Patient feature values highlighted in visual representation.

Feature	**Value for positive**	**Value for negative**
Pregnancies	11	4
Glucose	143	103
Blood Pressure	94	60
Skin Thickness	33	33
Insulin	146	192
BMI	36.6	24.0
Diabetes Pedigree Function	0.254	0.966
Age	51	45

To further increase representational richness, the grayscale fringe images were transformed into RGB format by applying distinct phase shifts to each color channel. Each channel encodes a phase-displaced version of the base pattern, resulting in higher visual complexity and providing CNNs with richer spatial and frequency cues. This systematic transformation was applied to the entire dataset, generating 1,000 images at a resolution of 224×224 pixels.

Following dataset preparation, an 80–20 split was performed for training and testing. Seven CNN architectures—LeNet, AlexNet, VGG, GoogleNet, DenseNet, ResNet18, and ResNet50—were trained to evaluate the classification performance of the proposed approach. Their results, compared to the baseline rectangular encoding proposed in [5], are summarized in Table 3.

Table 3. Classification performance of structured data by using visual representation.

Model	Accuracy (Gray)	Accuracy (RGB)
Baseline	80.8%	N/A
LeNet	81.0%	82.0%
AlexNet	70.0%	70.0%
VGG	80.0%	**82.5%**
GoogleNet	79.0%	79.0%
DenseNet	75.5%	75.5%
ResNet18	81.5%	81.0%
ResNet50	**83.5%**	82.0%

The summarized results highlight that ResNet50 achieved the highest classification accuracy, with 83.5% for grayscale and 82.0% for RGB representations. Its consistent performance demonstrates the architecture's ability to capture and generalize complex spatial cues introduced by Moiré fringe transformations. VGG also showed strong results, achieving 80.0% on grayscale images and an improved 82.5% on RGB, confirming the advantages of phase-shifted multichannel encodings [20].

Other architectures also outperformed the baseline, such as VGG, which reached 82.5% on RGB, and LeNet, which improved from 81.0% on grayscale to 82.0% with RGB images. These results confirm that multichannel (RGB) encodings enhance feature diversity and benefit CNN models. In contrast, AlexNet achieved only 70.0% in both grayscale and RGB, evidencing insufficient depth to capture the complexity of the transformed data. Overall, the comparison highlights that CNN-based classifiers, particularly ResNet50 and VGG, consistently exceed the performance of the baseline method (80%), validating the advantage of the proposed visual representation over traditional classification approaches.

Overall, these findings confirm that Moiré fringe encoding, especially in RGB format, enhances CNN classification performance for structured clinical data. The results support the hypothesis that visual encodings can reveal spatial relationships hidden in tabular datasets, thereby offering a disruptive perspective for data science applications in healthcare and beyond.

5. Conclusions

This study demonstrates that converting structured data into visual representations through Gaussian surfaces and Moiré fringe patterns significantly enhances classification performance when processed by convolutional neural networks (CNNs). By reframing tabular records into images, visual encoding uncovers hidden spatial and textural relationships that conventional numerical methods often overlook. This approach highlights the disruptive potential of data science, as it enables the application of computer vision techniques in contexts traditionally limited to statistical or tabular analysis.

Among the evaluated models, ResNet50 achieved the highest accuracy, particularly with RGB-encoded Moiré images, where phase variations across color channels enriched the representational space and improved feature learning. These results suggest that multichannel visual encodings can act as a disruptive transformation strategy, offering CNNs the ability to capture complex and clinically relevant patterns, and inspiring new directions for data-driven innovation in machine learning research.

Compared to the baseline rectangular encoding, the proposed methodology consistently outperformed traditional classifiers. This confirms the viability of integrating disruptive image-based representations into structured data pipelines, with promising implications for decision-support systems in healthcare, finance, and industrial applications. Ultimately, the findings reinforce the role of data science as a catalyst for cross-domain breakthroughs, leveraging visual paradigms to transform how structured datasets are analyzed and interpreted.

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