A Comprehensive Review of CNN Based Image Classification for Egg Fertility Detection

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ABSTRACT

The integration of technology into agriculture, particularly in poultry farming, has transformed processes like egg fertility detection, which is critical to improving both productivity and economic viability. This paper reviews the evolution of Convolutional Neural Networks (CNNs) as a non-invasive solution for egg fertility detection, focusing on their growing application in automating this traditionally labour-intensive task. Conventional methods, such as candling and chemical testing, are discussed, with attention to their historical importance and inherent limitations in accuracy and scalability. Early efforts in automating egg fertility detection, utilizing techniques like ultrasound, electrical conductivity, and visible transmission spectroscopy, are analysed to highlight their advancements and ongoing challenges. CNNs have revolutionized image classification and, in recent years, have shown significant promise in egg fertility detection. The paper covers the architecture and function of CNNs, detailing models such as LeNet-5, Mask R-CNN, YOLO, Transfer learning the latest DPSA network. Each of these models is evaluated for its accuracy, efficiency, and ability to differentiate between fertile and non-fertile eggs. A comparative analysis demonstrates the superiority of CNN-based approaches over traditional methods, emphasizing improvements in detection speed, reliability, and the potential for large-scale application in poultry farming. The review concludes by exploring future research directions, focusing on the potential of CNNs to further enhance non-destructive fertility detection methods. The need for continuous innovation in automated systems is underscored, particularly as the global demand for poultry products grows and as inefficiencies in current detection methods, including the economic impact of unfertilized eggs, drive the need for more accurate, scalable solutions.

Keywords: CNN based egg fertility detection, egg fertility detection, Poultry Industry.

1 Introduction

Poultry farming is an integral component of the global agricultural landscape, contributing significantly to food security, economic stability, and nutritional enhancement [1]. As one of the most efficient and sustainable sources of protein, poultry products especially eggs play a crucial role in diets worldwide. With the increasing global population and rising demand for poultry products, optimizing egg production processes has become imperative [2-3]. A fundamental aspect of this lies in effective egg fertility detection, which ensures that the eggs produced are viable and contribute to the overall productivity of poultry operations. Egg fertility detection encompasses various methods aimed at determining whether an egg is fertilized, a critical factor in successful hatchery operations. Traditional, methods such as candling—where eggs are held up to a light source to observe embryo development and chemical testing have been employed. While these techniques have served poultry farmers for many years, they present notable limitations in terms of accuracy, labour intensity and the potential for human error. The inability to reliably assess a large volume of eggs swiftly can lead to significant economic losses, particularly given that studies indicate approximately 30% of eggs produced may be unfertilized. This not only results in wasted resources but also affects the overall efficiency of poultry farming operations. Recognizing the need for more efficient and accurate systems, researchers have explored various automation techniques for egg fertility detection. Early

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methods, such as ultrasound technology [4], electrical conductivity measurements [5], and visible transmission spectroscopy [6], have laid the groundwork for modern approaches but have often struggled to meet the demands of large-scale production. In light of these challenges, the introduction of Convolutional Neural Networks (CNNs) has emerged as a game-changer in the field of image classification, offering a novel approach to egg fertility detection that leverages advanced machine learning techniques [7-8]. This paper aims to explore the various CNN models developed for egg fertility detection, beginning with an overview of CNN architecture and progressing through the adaptations of models like LeNet-5[9], Combining heartbeat and CNN [10], Mask R-CNN [11], YOLO [12], Transfer learning algorithms [13] and the latest DPSA network [14]. By comparing these models, this report seeks to highlight their advantages over traditional methods and illustrate their potential to transform poultry farming practices. Furthermore, the discussion will encompass the accuracy and limitations of these models, providing a comprehensive understanding of how CNNs can address the pressing challenges faced in egg fertility detection and contribute to the future of poultry farming.

2. Materials and Methods

2.1 Egg Fertility Detection

Egg fertility detection refers to the process of determining whether an egg contains a viable embryo that will develop into a chick. This is a crucial step in poultry farming, especially in large-scale operations.

2.2 Fertility Discrimination of Eggs Using Ultrasound

The study aimed to develop an image-processing system for monitoring the fertilization and growth stages of chicken embryos using ultrasonographic imaging techniques. A total of 189 eggs were incubated at a controlled temperature of 38°C and a humidity level of 70% [4]. The experimental setup involved three repetitions with nine eggs for each technique, resulting in 1,000 ultrasonographic images. The imaging process utilized an ultrasound device equipped with a phased probe emitting ultra sound signals to capture images of the embryos. Due to the calcium shell's opacity, a small hole was created in the air cell using an ovoscope to facilitate ultrasound penetration. The resulting ultrasonographic images were transferred to a computer for evaluation and subsequently resized to 32x32 pixels for use in a machine learning classification algorithm. Logistic regression was employed to classify the fertilization status of the eggs based on the processed images. This methodology highlights the innovative integration of imaging technology and machine learning for enhanced monitoring of embryo development and fertilization detection. The measurement was made between 3-10 MHz and the model accuracy is measured as 85.57.

2.3 Electrical conductivity Method

The study employed electrical conductivity as a non-invasive technique for distinguishing fertile, infertile, and non-viable embryo eggs before hatching. Two parameters were observed: the dielectric constant and the loss factor. In the experiment, Ross strain eggs were incubated in a fully automatic device with a holding capacity of 420 eggs, at 37.2°C and relative humidity of 70%, and eggs rotated once every hour [5]. On the 5th and 18th days of incubation, results showed that of 27 eggs, 21 were fertile and 6 were infertile. On transfer after incubation, 13 of the fertile eggs suffered embryo mortality, while the rest of the eggs hatched successfully. To determine capacitance, a specially designed electrical circuit was employed comprising a power supply, an AVR microcontroller, a sine wave generator (MAX038), a dielectric measurement integrated circuit (AD8302), a personal computer interface, and a capacitive sensor (as indicated in Fig. 1).

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Plates of a capacitor made of aluminum were set 30 mm apart to position the eggs. The sine wave generator had a frequency range of 40 kHz to 20 MHz, producing up to 192 sine waves per second. The voltage output of the capacitive sensor was checked for phase shift and attenuation, allowing for calculation of the eggs' dielectric properties and loss factors. Information collected were methodically organized in Excel and then analyzed using WEKA software to predict egg fertility status from electrical conductivity. The method provided an overall accuracy rate of 86.3%.

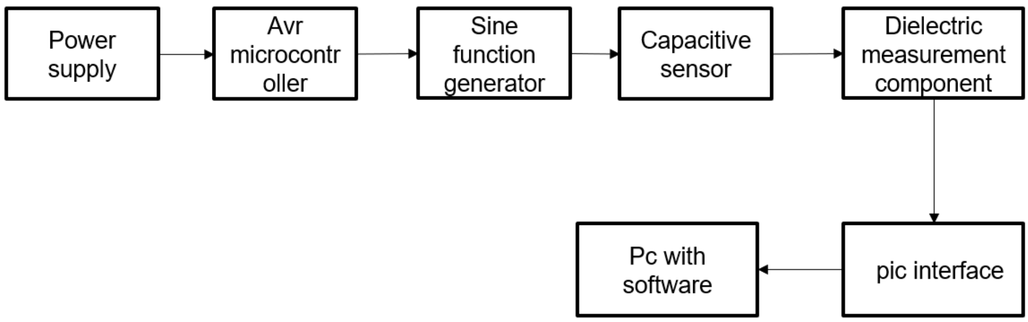

Figure1: *Block diagram of conductivity method*

2.4 Detection of infertile eggs using visible transmission spectroscopy

In this study, 165 light brown-shell Ross 308 chicken eggs were collected from a Japanese poultry hatchery. Eggs with similar shell colour, size, and weight were selected and stored for three days at 15°C and 80% humidity before incubation. Transmission spectra were measured using a halogen light source and a spectrometer over a 200–950 nm range, with 10 scans per egg to minimize variability. Calibration was performed regularly to maintain accuracy. Before incubation, eggs were preheated for 16 hours, and spectral measurements were taken. Incubation was conducted at 37.8°C and 55% humidity, with hourly automatic turning [6]. Spectral measurements were repeated every 24 hours until 144 hours, after which fertility was confirmed by candling and opening the eggs. Distinct spectral differences between fertile and infertile eggs emerged over time, particularly at 570–580 nm due to haemoglobin absorption in embryonic blood.
A significant drop in transmission at 589 nm and 643 nm was linked to the protoporphyrin pigment in the eggshell. After 96 hours, spectral shifts reliably indicated embryonic development, confirming that spectral data can effectively distinguish fertile from infertile eggs.

2.5 The Need for Automated Detection Systems

In traditional manual egg detection methods, a significant portion of eggs, typically around 20-30 percentage are un fertilized. This leads to a considerable amount of waste and financial loss for poultry farms. For example, in a batch of 1,000 eggs, 30 percentage are found to be unfertilized, that amounts to 300 eggs going to waste. With each egg costing rupees 5.5, this translates to a direct loss of rupees 1,650. When scaling up to larger operations, such as 10,000 eggs, the impact is even more substantial, with 3,000 wasted eggs resulting in a loss of rupees 55,000. Beyond financial repercussions, the process also consumes time and resources, as labour and incubation efforts are spent on eggs that will never hatch. This inefficiency reduces overall farm output, slows down production cycles, and significantly lowers operational efficiency, creating a ripple effect that hampers productivity. Effective automation methods, such as CNN-based detection, can significantly mitigate these losses by improving accuracy, reducing waste, and enhancing farm profitability.

2.6 Convolution Neural Network

A Convolutional Neural Network (CNN) is a complex deep network architecture specifically designed for visual data processing, i.e., images and videos. Its usage in image classification, object detection, and image segmentation can be explained by its ability to learn automatically and extract features from raw input. The key building elements of a CNN include convolutional layers, pooling layers, fully connected layers, and activation functions. Convolutional layers involve a set of filters (or kernels) that pass over the input image to detect important features, e.g., edges, texture, and patterns. These filters perform a convolution operation and produce feature maps showing the presence of certain visual features. Typically, the initial layers of the network are better at detecting simple features, e.g., edges or lines, while subsequent layers are tasked with detecting more complex representations, e.g., shapes or particular objects.

Pooling layers are located after convolutional layers and are tasked with reducing the spatial size of feature maps. This process of downsampling is extremely crucial in reducing the computational complexity of the model while, at the same time, maintaining important information. Some of the common methods used are max pooling and average pooling—max pooling captures the maximum value in an area, as compared to average pooling, which calculates the mean value of the elements in the area. After several convolution and pooling operations, the architecture has fully connected layers that examine the high-level features produced in the earlier layers. These layers operate in a similar way as traditional neural networks, whereby each neuron is connected to all the neurons in the next layer, thus enabling end predictions such as the classification of an image into categories such as fertile or infertile, as shown in Fig. 2. To facilitate the model to learn sophisticated patterns, the activation functions such as ReLU (Rectified Linear Unit) and Sigmoid are used after every layer. The non-linear functions allow the network to identify high-level relationships in the input data, thus improving its ability to generalize across various visual environments [7].

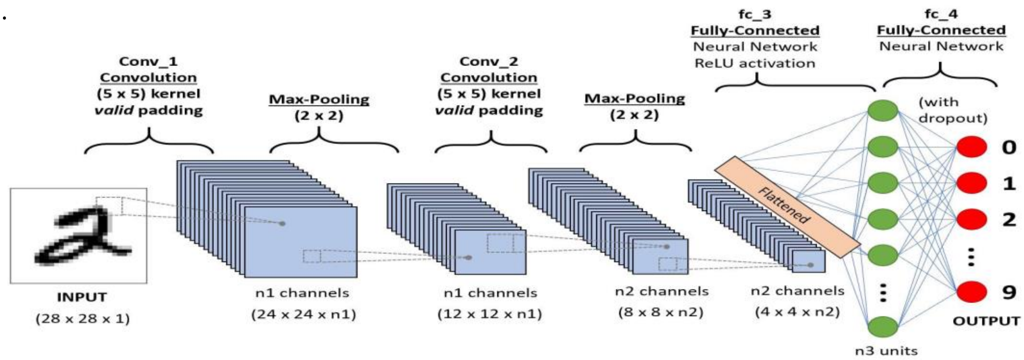

Figure.2: *CNN Architecture [7]*

2.7 Introduction of CNN In Egg Fertility Detection

In 2018, a CNN model was introduced to automate the traditional candling process for egg fertility detection, improving consistency over manual methods. The model processes candled egg images through convolutional layers, detecting key features like textures and shapes. ReLU activation enhances pattern recognition, while max pooling reduces dimensionality and computational complexity. Fully connected layers classify eggs as fertile or infertile. The model was trained on a labelled dataset with augmentation techniques like flipping and rotation, achieving an accuracy of 80-85%. However, challenges such as variations in shell thickness, lighting conditions, and high computational demands limit its scalability for large hatcheries.

2.8 LeNet-5 Adaptation for Egg Fertility Detection

LeNet-5, originally designed for digit recognition, was adapted in 2019 for egg fertility detection. It uses two convolutional layers and average pooling to identify internal structures like yolks and embryonic development. This adaptation improved efficiency while maintaining an accuracy of 88-92%. However, its shallow architecture limits its ability to capture complex fertility indicators, making it less effective for high-resolution or large-scale datasets. While computationally efficient, LeNet-5 struggles with scalability and may require modifications to handle real-time processing in large hatcheries [9].

2.9 Novel Method of Combining CNN and a Heartbeat Signal

Egg fertility detection using heartbeat signals is achieved through Photo Plethysmography (PPG), where a laser passes through the egg, and a sensor captures the transmitted light as shown in Fig 3. This signal is then digitized and processed via SPI for analysis. Since heartbeat signals are inherently noisy, standard CNNs struggle to extract relevant features effectively.

To overcome this, an E-CNN was developed with five convolutional layers, two pooling layers, and a fully connected layer to classify heartbeat sequences [10]. Further improvements were made using SE-Res CNN,

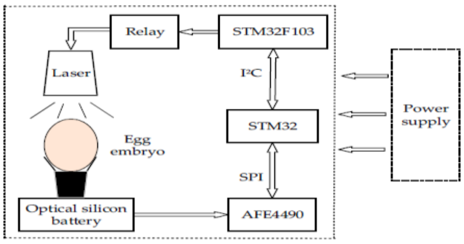

Figure.3: *Data acquisition method [10]*

which incorporates Squeeze-and-Excitation (SE) blocks for better feature attention and residual connections to improve gradient flow and training stability. These enhancements help filter out noise while focusing on relevant features, leading to superior classification performance. With these advancements, E-CNN achieved an accuracy of 99.50%, while SE-Res CNN reached 99.62%, making them highly efficient and reliable solutions for egg fertility detection.

2.10 Mask R-CNN To Detect Fertile and Infertile Eggs

A deep learning system based on Mask R-CNN is employed for classification, detection, and segmentation of fertile and infertile eggs in a single platform. The imaging is provided by a mounted camera system on the incubator, where uniform illumination is provided by power LEDs located under the vessels, as shown in Fig. 4. The image acquisition is controlled by an onboard minicomputer, and the computational efforts required in image processing are conducted by a high-performance workstation. Mask R-CNN operates through two basic steps: segmentation and classification. During the segmentation step, the RoIs are identified and pixel-level masks are generated, which are crucial for end-to-end feature extraction. Subsequently, the classification step processes these segmented regions to determine the fertility of each egg. The study utilized 24 egg images and developed two datasets of 5 and 18 viable eggs. The model exhibited outstanding performance, whose accuracy ranged from 95–98%, indicating its high potential for accurate and automatic egg fertility testing with the aid of deep learning and computer vision technology [11].

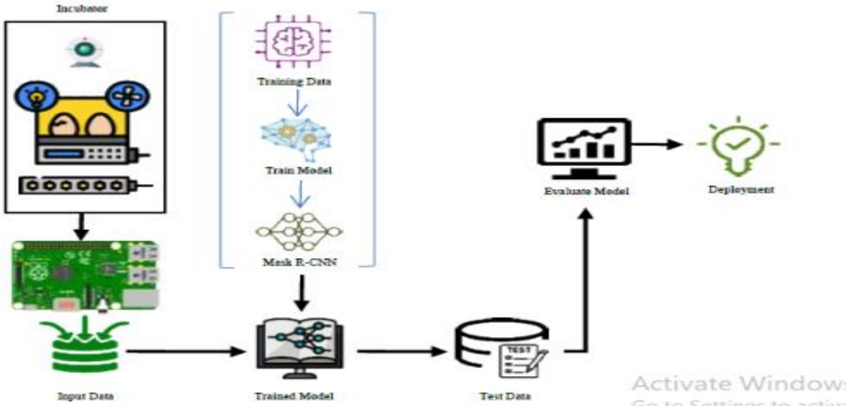

Figure.4: *Working phase of mask R-CNN method [11]*

2.11 Early Embryo Detection Using Thermal Micro Camera and The YOLO Deep Learning Algorithm

The YOLO algorithm is a groundbreaking object detection technique that is highly regarded for its speed of processing and image classification accuracy. Unlike conventional methods that specify the order of the region proposal and classification processes, YOLO converts object detection into a single regression problem where a single Convolutional Neural Network (CNN) is used to predict object classes and their respective bounding boxes simultaneously. This dual approach facilitates performance in real-time detection. YOLOv4, a more refined version of the algorithm, is implemented utilizing Darknet—a free C and CUDA-based neural network library. Utilizing thermal and optical images acquired with thermal imaging technology for egg fertility detection, YOLO is applied as described in Fig. 5. The model identifies unique patterns like the visible "chamber" formation that can be seen in fertilized eggs. The training process entails annotated datasets that result in either fertile or infertile classification, and optimization is carried out using backpropagation. To enhance its robustness and generalizability, various data augmentation techniques—image rotation, flipping, and zooming—are utilized while training. With this approach, YOLO models usually achieve classification accuracy rates of above 95%, thereby attesting to their effectiveness in the accurate and efficient detection of fertile eggs [12].

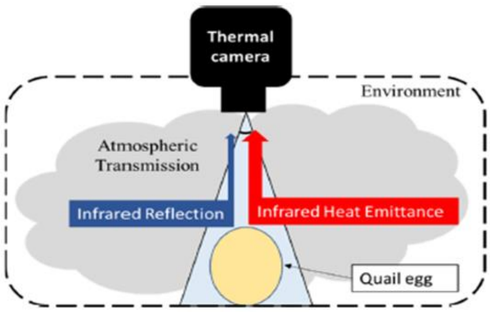

Figure.5: *Thermal camera environment [12]*

2.12 Egg Fertility Detection Using CNN-Transfer Learning Algorithms

The CNN-Transfer Learning approach was applied for non-destructive chicken egg fertility detection using VGG16, ResNet50, Inception Net, and Mobile Net models. A dataset of 200 labelled images, equally split between fertile and infertile eggs, was captured using the egg candling method in a controlled dark room with a 13 MP smartphone camera. Pre-processing involved cropping and segmentation to isolate relevant features, followed by data augmentation techniques such as rotation, flipping, scaling, translation, and reflection to improve model generalization. Given the limited dataset, transfer learning was utilized to fine-tune pre-trained CNN models. Throughout training, all models demonstrated improvements in accuracy and loss reduction, with final accuracy values of 98.03% for VGG16, 98.0% for ResNet50, 98.04% for Inception Net, and 98.04% for Mobile Net. These models effectively classified fertile and infertile eggs with high precision, making them viable for improving accuracy in poultry hatchery practices [13].

2.13 DPSA Network for Egg Fertility Detection

The Dense Pixelwise Spatial Attention (DPSA) network enhances egg fertility detection by employing advanced attention mechanisms to focus on critical image features. Its spatial attention mechanism assigns pixelwise weights, improving sensitivity to subtle variations in colour and texture indicative of embryonic development. Channel-wise attention, achieved through squeeze-and-excitation (SE) mechanisms, further refines feature selection by emphasizing informative details. DPSA utilizes depth wise separable and dilated convolutions to maintain spatial resolution without losing crucial information. Unlike traditional methods, it preserves fine details essential for accurate classification.

The egg imaging system includes a sterile dark box, an LED light source for consistent illumination, and high-resolution industrial cameras. Images undergo binarization and edge detection to enhance quality. DPSA generates fine-grained saliency maps that highlight significant features while suppressing noise, improving classification accuracy. Ablation experiments demonstrated DPSA's effectiveness, achieving 98.3% accuracy for 5-day-old embryos and 99.1% for 9-day-old embryos [14] shown in Fig.6 . By integrating DPSA with SE-Net, the model enhances feature representation and improves classification performance.

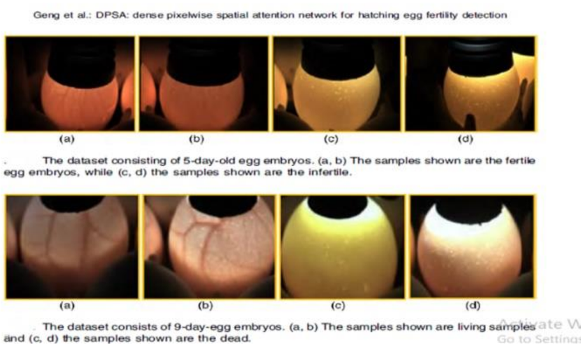

Figure.6: *Result from 5- and 9-days old egg [14]*

These advancements contribute to automation in poultry farming and have broader applications in agriculture, such as disease identification and livestock monitoring, ensuring efficiency and quality in modern production systems.

3. Results and Discussion

The results demonstrate that CNN-based models significantly outperform traditional egg fertility detection methods in terms of accuracy and efficiency. While conventional techniques such as ultrasound and electrical conductivity achieved moderate accuracy levels of around 85-86%, advanced deep learning models like Mask R-CNN, YOLO, and DPSA networks exhibited superior performance, reaching accuracies above 95%. The integration of physiological data, such as heartbeat signals, further enhanced detection capabilities, achieving nearly 99.5% accuracy. Refer table.1 for accuracy comparison. These findings highlight the transformative potential of CNN-based approaches in automating egg fertility assessment, reducing human error, and improving scalability for large-scale poultry operations. The DPSA network, in particular, showcased exceptional precision through its spatial attention mechanism, making it a promising solution for real-time applications. Despite these advancements, challenges such as computational complexity and variations in imaging conditions remain, emphasizing the need for further model optimization and hardware efficiency improvements. Overall, CNN-driven methods present a revolutionary shift in fertility detection, offering the poultry industry a more reliable, automated, and cost-effective solution to enhance productivity and reduce resource wastage.

Table 1. Comparison of different fertility detection methods

Detection models	Accuracy
Fertility Discrimination of Eggs Using Ultrasound	85.57
Electrical conductivity Method	86.3
Detection of infertile eggs using visible transmission spectroscopy	87.3
Basic CNN Method	80-85
LeNet5 Method	88-92
CNN and heartbeat	99.50
Mask R-CNN	95-98
Yolo	95
Transfer learning	98
DPSA	98-99.1

4. Conclusions

This paper explored the critical role of CNN-based image classification in egg fertility detection, which is essential for optimizing poultry farming. Poultry farming, a cornerstone of global food production, depends on efficient fertility detection to maximize hatchability rates, minimize waste, and ensure economic viability. As global demand for poultry products continues to rise, accurate and reliable fertility detection is becoming increasingly crucial for meeting production goals. Traditional methods, such as egg candling and chemical testing, exhibit significant limitations including labour intensity, human error, and low accuracy, with approximately 20-30% of eggs unfertilized. These inefficiencies lead to considerable financial loss and resource wastage. The need for automation in the industry is driven by these shortcomings, as well as the growing scale of modern poultry operations. Early automation methods, including ultrasound, electrical conductivity, and visible trans mission spectroscopy, improved accuracy over manual techniques but still fell short in eliminating unfertilized eggs. This highlighted the need for more advanced systems, capable of delivering real-time and large-scale egg assessment with minimal human intervention. CNNs have emerged as a ground-breaking solution for egg fertility detection due to their superior image classification capabilities. The paper discussed various models, from early architectures like LeNet-5 to advanced models such as Mask R CNN, YOLO, and DPSA networks. These models progressively improved detection accuracy, with standing out for its precision in distinguishing between fertile and infertile eggs. In conclusion, CNN-based approaches significantly enhance egg fertility detection, reducing wastage and improving decision making for poultry farmers. Future advancements in CNN architectures and real-time monitoring could further revolutionize the field, promoting greater efficiency and sustainability in poultry farming. Integrating these technologies at scale could lead to a more productive, cost-effective, and environmentally sustainable poultry industry.

5. Declarations

5.1 Competing Interests

The authors declare that they have no competing interests

5.2 Acknowledgements

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