

# From Noise to Readable Images



Eavesdropping on Computer Screens via Custom Hardware and Deep Learning Image Reconstruction

## Video Transmission Interfaces

Several **video transmission interfaces** are used to deliver image data from a computer to a display device. These include **analogue** and **digital** formats, each with signaling methods that can be **susceptible to electromagnetic leakage**.

### Analogue (VGA)

- Maps each **pixel's R, G, and B intensities** to corresponding **voltage levels**
- Pixels are transmitted as **horizontal scan lines**, synchronized by the **HSync** signal
- These scan lines form complete **image frames**, aligned using the **VSync** signal
- The process repeats continuously to produce the displayed image
- HSync** and **VSync** signals are transmitted together with **blank pixels**, creating **padding** around the visible image area

### Digital (HDMI)

- Transmits each pixel's **R, G, and B intensities** using **Transition-Minimized Differential Signaling (TMDS)**
- 8-bit color values** are encoded into **10-bit TMDS symbols**
- These symbols are sent as a **high-speed serial data stream**
- The display device converts the **10-bit TMDS symbols** back into **8-bit color values**
- Displayed image is aligned using **embedded synchronization signals**, analogous to **HSync** and **VSync** in VGA

## Van Eck's Radiations

The principle behind the attack is that image transmission relies on **rapid voltage transitions** to represent pixel colour intensities. These transitions unintentionally emit **electromagnetic radiation** in the **VHF (30–300 MHz)** and **UHF (300 MHz–3 GHz)** radio bands [1].

### Pixel Timing

For **VGA**, the pixel transmission period is

$$t_p = 1/(x_t \cdot y_t \cdot f_v)$$

where  $x_t$  is the display width,  $y_t$  is the display height, and  $f_v$  is the display frame rate.

For **HDMI**, where each pixel intensity is represented using  $n_b$  bits, the bit transmission period is

$$t_b = 1/(x_t \cdot y_t \cdot f_v \cdot n_b)$$

### Inference of Pixel Colour

In **VGA**, voltage transitions generate **RF impulses** at the multiples of  $t_p$ . The **impulse amplitude** corresponds to the **grayscale intensity** of the transmitted pixel.

In **HDMI**, where **RF impulses** occur at the multiples of  $t_b$ , the pixel's **grayscale intensity** can be inferred by **averaging the bit-level signal** over each pixel transmission period.

## TempestSDR

Eavesdropping on a display device can be executed using **TempestSDR**, an open-source software-defined radio application, capable of **reconstructing images in real time** from captured electromagnetic emissions [2].

In addition to the reconstruction, it provides **automatic detection of the target display's resolution and frame rate**, a feature essential for carrying out the attack.

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Baseline Attack

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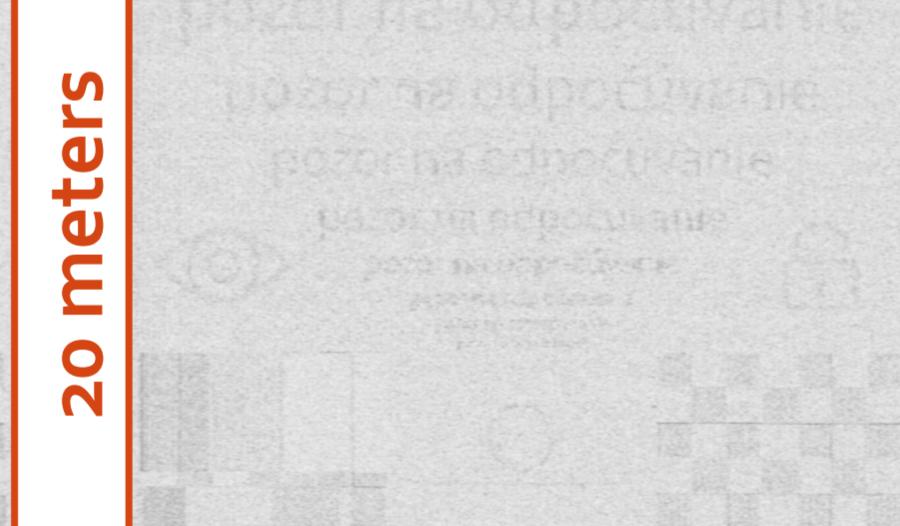
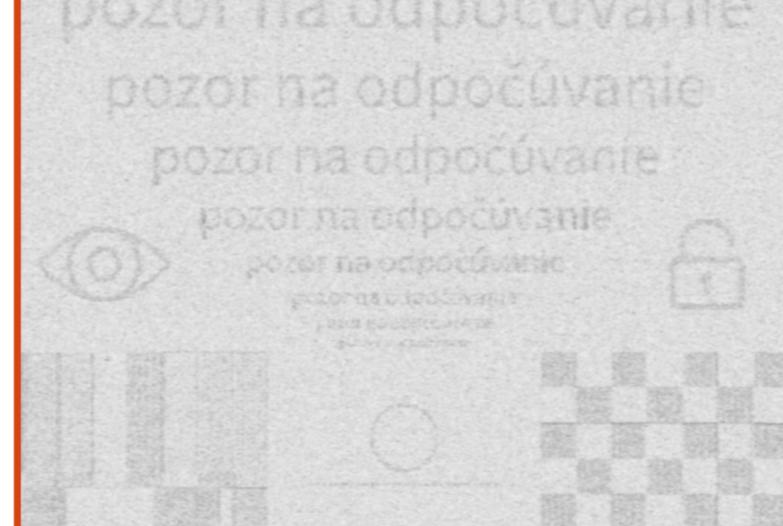
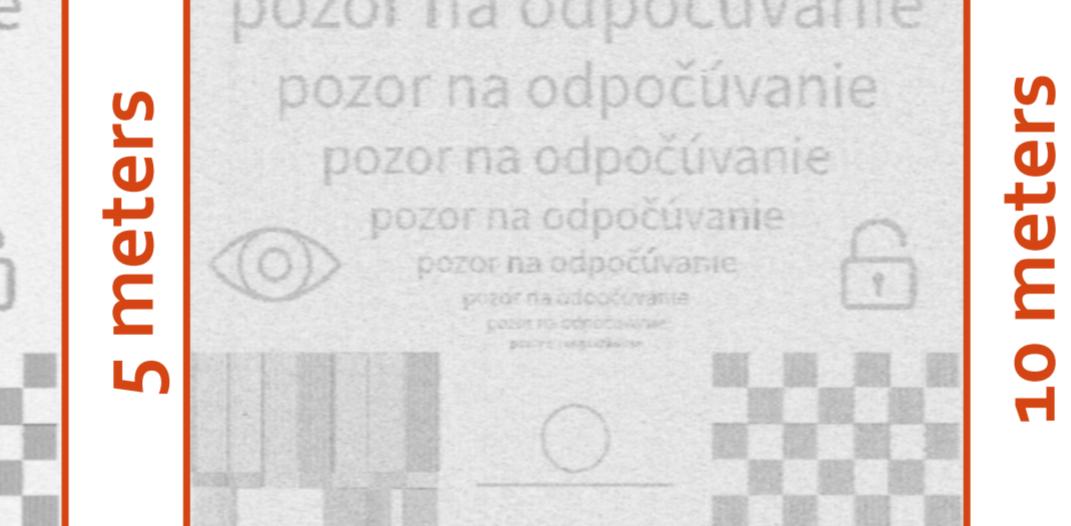
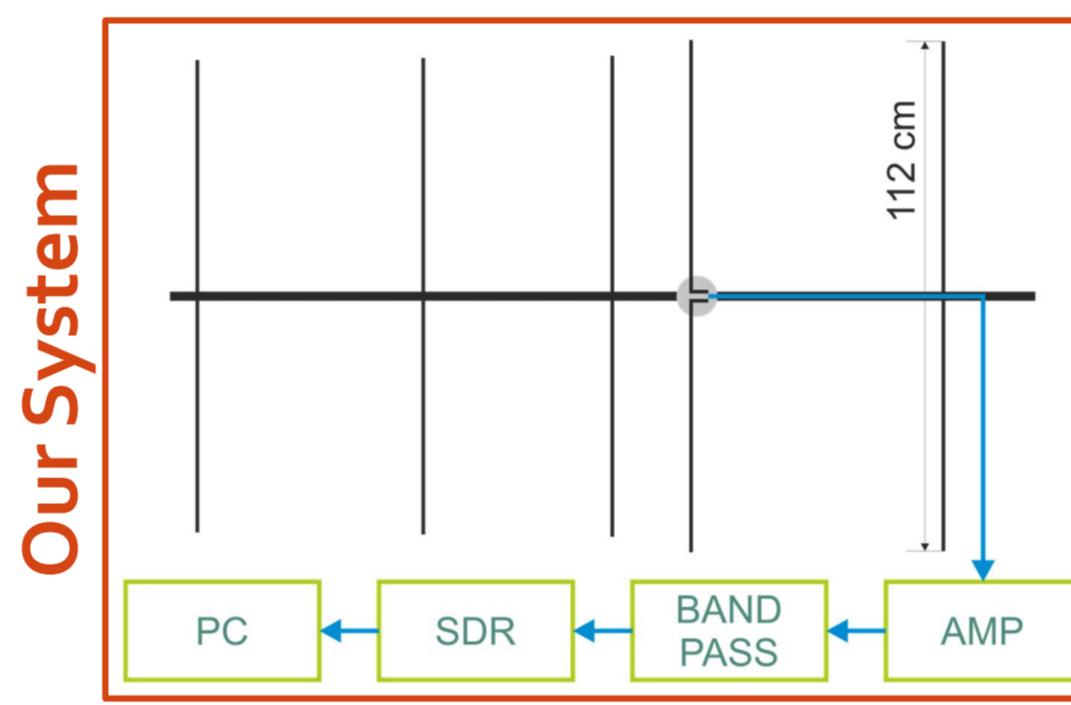
## Custom Hardware

### Extending the Range of Attack

The effectiveness of electromagnetic eavesdropping strongly depends on **hardware performance**. Using only standard equipment — specifically an **omni-directional antenna** — we found that the practical capture range was limited to **approximately 1 meter**.

To extend this range, we employ a **high-gain directional Yagi-Uda antenna**, a **low noise amplifier (LNA)**, and a **band-pass filter**. The hardware was tuned to **130 MHz** and evaluated from various distances.

With optimized hardware, the capture range increased **from 1 meter to 20 meters**.



## Deep Learning Image Reconstruction

### Recovering the Images

Even with optimized hardware, reconstructed images remain **noisy and distorted**. To address this issue, we applied **deep learning** techniques for **image post-processing and enhancement**.

### Dataset

- 650 real **ground-truth** images from desktops, popular websites, and graphical user interfaces
- 200 generated **ground-truth** images with random text (varied fonts and sizes) to improve **text legibility**
- Each ground-truth image has **~6 captures** with different **antenna distances and orientations**
- Captures include both **VGA** and **HDMI** emissions, simulating real-world variations
- Padding was removed** with template matching
- Split the dataset in 80:10:10 ratio into training, validation, and test subsets
- Whole process was **automated** using PyAutoGUI, Selenium, and OpenCV

### DnCNN

- CNN designed for **image denoising**
- Trained to predict the **residual image** (noise map)
- Clean image obtained by **subtracting** the predicted residual image from degraded image
- Features **17 convolutional layers**

### DRUNet

- CNN designed for **general image restoration tasks**
- Trained to predict the **clean image**
- Based on the **U-Net architecture**, with a **4-level encoder-decoder** and skip connections
- Proven use in the **Deep-Tempest** project [3]

### Training

- From **scratch** on the train subset for 100 epochs
- Input images were split into **256x256 pixel patches**
- Batch size** set to 32
- Adam Optimizer** was utilized

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### Results

Evaluated using image quality and text legibility metrics

- Peak Signal-to-Noise Ratio (PSNR)
- Structural Similarity Index Measure (SSIM)
- Character Error Rate (CER)

Method	PSNR	SSIM	CER
TempestSDR	8.65 dB	0.41	86 %
DnCNN	17.63 dB	0.75	54 %
DRUNet	19.08 dB	0.87	46 %

### References

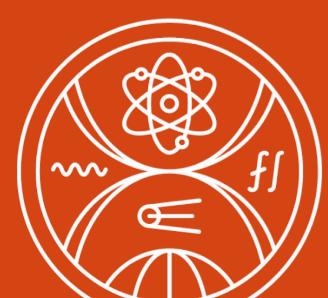
- [1] VAN ECK, W. *Electromagnetic radiation from display units: An eavesdropping risk?* Computers & Security. 1985, 4(4), 269–286.
- [2] MARINOV, M. *TempestSDR – Remote eavesdropping using a software-defined radio platform*. GitHub repository, 2025. URL: [github.com/martinmarinov/TempestSDR](https://github.com/martinmarinov/TempestSDR)
- [3] FERNANDÉZ, S. et al. *Deep-Tempest: Using Deep Learning to Eavesdrop on HDMI from its Unintended Electromagnetic Emanations* [preprint]. 2024. arXiv:2407.09717.

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