CellCast: The 3.5-Hour Test for mRNA Medicines, by Anusha Bassi

Introduction and Background: Biology 12 taught me that cell membranes block most molecules, so I wondered how my own COVID-19 vaccine got in. The answer is lipid nanoparticles (LNPs), tiny fat bubbles; the Pfizer-BioNTech ones came from a UBC spin-off.[1] Progress is slow: only a small part of cargo escapes into the cell,[2] each lab test takes 12 hours,[3] and a 2024 PNAS review calls for faster methods.[2] CellCast extends my CWSF 2026 project.

Innovation: CellCast is an AI tool I designed: it watches a cell's first 3.5 hours of microscope images, predicts its protein output at hour 12, with a heatmap of what it looked at.[5] Other AI tools judge LNPs by chemistry alone[4] or give no explanation.[3]

Procedure: Using a public Uppsala University and AstraZeneca dataset of 774 liver cells filmed for 12 hours,[3] I designed my own six-part architecture, not an off-the-shelf model: a shared frame encoder, position encoding, a two-layer Transformer[6] comparing all 20 frames at once, a learned pooling layer that weights timepoints, and Grad-CAM[5] wired in. Only the frame encoder is pretrained;[7] every temporal part is mine. I taught myself PyTorch and built four prototypes.

Results and Observations: On the same 172 unseen test cells as the published model[3], CellCast's error was 13.9% lower (0.517 vs ≈ 0.60; 95% CI below 0.60). Heatmaps were significantly more focused in high-protein than low-protein cells ($p < 0.03$), showing that CellCast locks onto one tight region when delivery succeeds.

Conclusion: Answers in 3.5 hours instead of 12 let one microscope screen three times as many designs per day for cancer vaccines and gene therapies. CellCast only pre-screens, so top designs still get the full lab test, and it uses no patient data. Next, I will ask BC LNP labs to test it on new formulations and cell types; success means ranking designs as 12-hour tests do.

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